Optimization-Based Selection of Influential Agents in a Rural Afghan Social Network

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Assignment

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Benjamin W. K. Hung, Major, U.S. Army Date

Table of Contents

1 Introduction 15

1.1 Research Motivation 15

1.2 Problem Statement 16

1.3 Technical Approach 17

1.4 Experimentation 18

1.5 Contributions 18

1.6 Thesis Organization 19

2 The Struggle for Popular Support in a Counterinsurgency 21

2.1 Popular Support in Insurgencies and Counterinsurgencies 21

2.1.1 Defining Popular Support 21

2.1.2 Forms of Popular Support 22

2.1.3 Moving Along a Spectrum of Support 23

2.2 Operational Environment (OE) in a Counterinsurgency 23

2.2.1 Operational and Mission Variables 24

2.2.2 Criticality of Civil Considerations 26

2.3 Insurgency 26

2.3.1 Generic Organization 26

2.3.2 Mechanisms of Mobilization 27

2.4 Counterinsurgency 28

2.4.1 Full Spectrum Operations 28

2.4.2 Lines of Effort (LOEs) 28

2.4.3 Planning Processes 31

2.5 Nonlethal Targeting in a Counterinsurgency 36

2.5.1 Targets and Nonlethal Activities 37

2.5.2 Functional Decomposition of Nonlethal Targeting Activities 38

2.5.3 Decide 41

2.5.4 Detect 44

2.5.5 Deliver 45
2.5.6 Assess 45
2.6 Case Study: Taliban Insurgency in Afghanistan 45
2.6.1 Some Aspects of the Afghan Operational Environment 46
2.6.2 Taliban Insurgency Summary 52
2.6.3 US Army COIN in Afghanistan 55
2.6.4 Difficulties in Nonlethal Targeting in Afghanistan 57
3 Modeling Approach and Formulation 59
3.1 Modeling approach 59
3.2 Related Literature 60
3.2.1 Social Science Literature on Opinion Leaders and Influential People 60
3.2.2 Opinion Dynamics Literature 61
3.2.3 Key Person Problem (KPP) Literature 63
3.2.4 Afghan Application of Network Modeling 63
3.3 Afghan COIN Social Influence Model 63
3.3.1 Scope of the Model 64
3.3.2 Agent Properties 65
3.3.3 Attitude Dynamics 67
3.3.4 Analytic Formulation of Expected Long-Term Attitudes 71
3.3.5 Network Connections 76
3.4 Network Generation Model 77
3.4.1 Inputs 78
3.4.2 Assumptions 78
3.4.3 Homophily Link Generator 79
3.4.4 Intelligence Cell Validation 79
3.4.5 Accounting for Random Connections 81
3.4.6 Output 83
3.5 Nonlethal Targeting Problem 83
3.5.1 Assumptions 83
3.5.2 Decision Variables--Actions/Controls 84
3.5.3 Derivation of Optimization Formulation 85

3.5.4 *Objective Function* 86
3.5.5 *Constraints* 87
3.5.6 *Simplifying the Formulation* 93

4 Experiments and Analysis 97

4.1 Implementation 97

4.1.1 *Agent Database* 97
4.1.2 *Network Generator* 97
4.1.3 *Monte Carlo Simulation* 98
4.1.4 *Optimization with AMPL and KNITRO* 98

4.2 Network Data and Other Parameters 99

4.2.1 *A Small Network* 100
4.2.2 *A Large Network* 103

4.3 Experiment 1 104

4.3.1 *Experiment 1A* 106
4.3.2 *Experiment 1B* 108
4.3.3 *Experiment 1C* 112
4.3.4 *Experiment 1 Conclusions* 114

4.4 Experiment 2 114

4.4.1 *Experiment 2 Design* 114
4.4.2 *Experiment 2 Results and Analysis* 115
4.4.3 *Experiment 2 Conclusions* 116

4.5 Experiment 3 116

4.5.1 *Experiment 3 Design* 116
4.5.2 *Experiment 3 Results and Analysis* 123
4.5.3 *Experiment 3 Conclusions* 132

4.6 Summary of Experimentation 133

5 Future Research and Application as a Decision Support Tool 135

5.1 Future Work 135

5.1.1 *More Realistic Dynamics* 135
5.1.2 *Short-term Expected Attitudes* 137

5.1.3 *Adversarial Actions and Game-Theoretic Approaches* 137
5.1.4 *Alternative Formulations* 137

5.2 Application as a Decision Support Tool 140

5.2.1 *Integration into Nonlethal Targeting* 140
5.2.2 *Data Collection* 142

6 Summary and Conclusions **145**

6.1 Summary 145

6.2 Conclusions 146

6.2.1 *Modeling Social Networks and Influences among Pasthuns* 147
6.2.2 *Merits of Optimization-Based Methods of Targeting* 147

Appendix A Abbreviation and Acronyms **149**

Appendix B Experimental Data and Results **151**

References **177**

List of Figures

Figure 2-1: Range of Popular Support [3] 23
Figure 2-2: Example Considerations within each ASCOPE category [3] 25
Figure 2-3: Counterinsurgency Lines of Effort[3] 29
Figure 2-4: Army Planning Processes Synchronization 32
Figure 2-5: Intelligence Preparation of the Battlefield[16] 34
Figure 2-6: Lethal and Nonlethal Targets in COIN [3] 36
Figure 2-7: Nonlethal Targeting Functional Decomposition 40
Figure 2-8: Decide Function 42
Figure 2-9: Generic Target Synchronization Matrix (TSM) 44
Figure 2-10: Ethnic Map of Afghanistan[23] 46
Figure 2-11: Pashtun Tribes and Sub-tribes [31] 48
Figure 2-12: Pashtun Local Leaders and Spheres of Influence 49
Figure 2-13: Survey Results of the Most Influential Person in the Neighborhood [44] 52
Figure 2-14: Survey Results of One's Own Opinion on who is Most Important [44] 52
Figure 2-15: Reported Sources of Information by Percentage [45] 52
Figure 2-16: Taliban Organizational Structure [31] 53
Figure 3-1: Functional Overview of the Models 60
Figure 3-2: Attitude Scale 67
Figure 3-3: Network Generation Model 78
Figure 3-4: Rewiring Procedure [87] 81
Figure 3-5: Nonlethal Targeting Problem Formulation 92
Figure 3-6: Revised Nonlethal Targeting Problem Formulation 96
Figure 4-1: A sample network generated from the 'islands' economic model[95] 100
Figure 4-2: A Small Network 102
Figure 4-3: Legend for Network Generator Graphs 102
Figure 4-4: A Large Network 104
Figure 4-5: Plot of Experiment 1A Runtimes by Case Number 108
Figure 4-6: Comparison of Runtimes for NLTP and NLTP1 Formulations for Select Case Numbers 110
Figure 4-7: Comparison of Runtimes for NLTP and NLTP1 for Various Multi-Start Settings 112
Figure 4-8: Experiment 3 Small Network (with Village Labels) 118
Figure 4-9: Experiment 3 Large Network (with Village Labels) 119
Figure 4-10: Experiment 3A Results-Performance of 3 Selection Methods in 8 Cases 124

Figure 4-11: Experiment 3B Results-Performance of 3 Selection Methods in 7 Cases 125
Figure 4-12: Experiment 3B, Case #7- Picture of Expected Long-Term Attitudes for Random Selection 126
Figure 4-13: Experiment 3B, Case #7- Picture of Expected Long-Term Attitudes for Doctrine-Based Selection 127
Figure 4-14: Experiment 3B, Case #7- Picture of Expected Long-Term Attitudes for NLTP Optimization-Based Selection 128
Figure 4-15: Experiment 3B, Case #7 Results-Plot of Averaged Mean Expected Long-Term Attitudes versus Interaction Number 129
Figure 4-16: Experiment 3B, Case #7-- 130
Figure 5-1: NLTP Decision Tool in the Targeting Process 140
Figure 5-2: NLTP Decision Tool Integration into the Decide Function 141
Figure 5-3: Example Tribal Questionnaire [98] 144
Figure 5-4: Example questionnaire for assessing influence and connections [99] 144

List of Tables

Table 3-1: Afghan COIN Social Influence Model Notation and Descriptions 75
Table 3-2: Homophily Rules Used in the Network Generation Model 80
Table 3-3: Parameters for the Forceful Influence-Type Probability for US Agents 88
Table 3-4: Parameters for the Self-Weight of Non-US Agents to US Agents 88
Table 3-5: Notation for Optimization Formulation 91
Table 4-1: Agent List and Characteristics in Small Network 100
Table 4-2: Intelligence-informed Connections in Small Network 101
Table 4-3: Summary of Experiment 1 106
Table 4-4: Experiment 1A Results 107
Table 4-5: Experiment 1B, Part 1 Results 109
Table 4-6: Experiment 1B, Part 2 Results 111
Table 4-7: Experiment 1C Results 113
Table 4-8: Experiment 2 Results 115
Table 4-9: Summary of Experiment 3 117
Table 4-10: Resource Level and Forceful Influence-Type Probability for US Agents 117
Table 4-11: Table of Cases for Experiment 3A 120
Table 4-12: Table of Cases for Experiment 3B 120
Table 4-13: Doctrinal Justification of Targeting Assignment in Experiment 3A 121
Table 4-14: Doctrinal Justification of Targeting Assignment in Experiment 3B 122
Table 4-15: Overall NLTP Agent Selection Analysis 131
Table 4-16: NLTP Agent Assignment Analysis by US Agent Resource Level (Forcefulness) 133

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1 Introduction

In this thesis, we describe a technical approach to assisting US Army units in deciding how to win support of populations in counterinsurgency conflicts. In this chapter, we present the motivation for this research, state the problem, and provide a synopsis of this thesis by describing our modeling approach and experimentation plan. We also specify our main contributions.

1.1 Research Motivation

Current US Army doctrine espouses that on-going and future threats to the United States are and will likely be the result of "nations unable or unwilling to meet the basic needs and aspiration of their people" ([1]: vi). Such fragile states, like Afghanistan, are prone to offer safe haven and training ground for terrorists and other extremists who can threaten the US at home. Consequently, the US has declared as part of its National Security Strategy an effort to help establish stable, well-governed nations, and made it likely that the US military will continue to operate in countries with weak governments in the future [1].

Insurgent movements, however, are often a natural consequence of weak governments. They rely on the broad support of the local population and seek to overthrow these governments by use of force. As a result, as shown in recent history, the US military finds itself conducting counterinsurgency operations on the side of these fledgling host nation governments, with the difficult dual tasks of defeating the insurgencies as well as strengthening the governments to better provide for and protect their people.

The key distinction between counterinsurgency and other forms of warfare is the primary means with which the army defeats the enemy. In counterinsurgencies, an army ultimately wins by gaining support of the population and *not* by killing or capturing insurgents alone. Since insurgents find grassroots support from among the population, excessive lethal operations by counterinsurgents are likely to engender resentment and a backlash that will fuel the insurgency [2]. Instead, counterinsurgents must conduct extensive *nonlethal operations*, a broad set of influencing actions that include engaging in constructive dialogue with local leaders as well as addressing root causes of poor governance by providing aid and reconstruction assistance for the people [3], to successfully gain support of the population. We define *local leaders* as those

individuals within the population who by virtue of their authority, power, or position have influence over the attitudes of a group of people. When counterinsurgents exploit the effect of these local leaders and achieve popular support, they deny the insurgents the ability to find the sanctuary and assistance that are critical to the movement's survival. Therefore, the focus in counterinsurgencies is nonlethal rather than lethal operations, a hard lesson the US military learned in the most recent counterinsurgencies in Iraq and Afghanistan.

1.2 Problem Statement

This thesis considers the nonlethal targeting assignment problem. This is the problem of deciding on the people whom US forces should engage "through outreach, negotiations, meetings, and other interactions" in order to ultimately win the support of the population in their area of operations ([3]: 4-28). In the counterinsurgency operations in both Iraq and Afghanistan, units of battalions and companies are assigned vast amounts of territory and often charged with winning the support of tens of thousands of people. These units, however, are also resource-constrained in some form or another, including personnel, money, equipment, and time. These constraints force units to be very selective in the number, type, frequency, and objective of the operations they conduct. What villages they patrol, where they perform reconstruction projects, and with which local leaders they conduct negotiations and outreach are just some of the daily questions that commanders and staffs have to answer.

Targeting is a planning process that guides commanders and their staff to both prioritize objectives and operations, and to synchronize the methods of engagement in order to accomplish the mission. However, because success or failure of conducting nonlethal targeting is contingent upon on human behavior and a whole set of known and unknown variables, it is extremely difficult to truly predict how a nonlethal action on an individual will affect a group of people and very challenging to value one target over another or the value of a group of targets. The current methods of prioritizing and determining target value are qualitative at best and often based upon the commanders' and staffs' intuition as well as their understanding of doctrine.

Given the tremendous difficulty of and the extreme importance placed upon nonlethal targeting in counterinsurgency (COIN), we offer an alternative quantitative approach to address how units can determine the best nonlethal targeting assignment strategies and how the sentiments of the population might change as a result of them.

1.3 Technical Approach

We utilize operations research methods to begin to find solutions to this very complex problem. Our ultimate goal is to develop a decision support tool that helps commanders and staffs make better decisions on whom to target nonlethally in order to achieve the most popular support while still operating within the unit's resource-constraints. In working towards this goal, we employ the following technical methods: social network analysis, tractable agent modeling, and network optimization.

Social network analysis is an interdisciplinary field of study that concerns the relationships among individuals or groups of people who are represented as nodes with ties on a network [4]. It is founded on the idea that humans are interconnected, and that in order to understand human behavior one must also understand the structure of the relationships among them. In this work in particular, we model the various actors in a counterinsurgency (local leaders and Taliban and US forces) as nodes and the relationships among them as ties on social network.

Tractable agent modeling is a modeling technique that *analytically derives* the emergent collective behavior from the individual decisions of a group of autonomous entities called agents. The agents are endowed with certain characteristics and interact with other agents based on a set of simple rules. This approach is in contrast to agent-based modeling, a simulation technique that can model complex human behavior [5] but seldom provides much analytic insight[1]. In our work, we model local leaders in Afghanistan as agents who repeatedly interact in a social network with other local leaders, and Taliban and US forces. Each agent possesses a scalar-value attitude of favorability towards US forces, as well as probabilities of influencing each of its neighbors' attitudes. We assume that local leaders change their attitudes (according to their neighbors' influence probabilities), while the Taliban and US forces do not. In the presence of these mutable and immutable agents, we not only explore dynamics of the attitudes of the entire population in simulation, but we also analytically derive a means to determine the expected long-term attitudes of all agents. This tractable model of agent behavior and interactions is based primary on the work of Asuman Ozdaglar and others ([6], [7]). Additionally, our model's tractability subsequently leads us to a computational framework for network optimization.

[1] The resulting collective behavior from agent-based simulation is often counterintuitive and "out of the reach from pure mathematical methods" ([5]: 7280).

Network optimization solves problems specifically formulated from a network graph and involves the minimization (or maximization) of an objective function subject to some constraints [8]. These problems can be linear or nonlinear, as well as continuous or discrete. In this work, we formulate a modification of the assignment problem, a major class of problems in network optimization that have been important in determining resource allocation and other areas [8]. Our nonlinear assignment problem solves for the assignment of US forces to local leaders and Taliban forces on a network that maximizes the arithmetic mean of the expected long-term attitude of the local leaders. The *expected long-term attitude* is the expected value of the random variable of long-term attitudes of each local leader. The *arithmetic mean* is over all local leaders.

1.4 Experimentation

For our experimentation, we develop a fictional but realistic data set of local leaders in a rural Afghan district. The first experiment focuses on determining the capabilities of the optimization model in terms of runtime on networks of various sizes. The second experiment analyzes the performance of the optimization model in finding globally optimal assignment strategies in a small number of cases where the complete enumeration of assignments is possible. Finally, in the third experiment, we compare the analytic and simulated performances of the optimization-based assignment strategy with US Army doctrinal and baseline (random) strategies.

1.5 Contributions

This thesis makes four main contributions. First, it applies existing research on tractable agent modeling of attitudes and interactions to the context of the counterinsurgency in Afghanistan. Second, it introduces a methodology for determining approximations of interpersonal influences as well as topologies of Afghan social interaction networks based upon social science and anthropological research. Third, it provides a consistent, quantitative method of determining the value of nonlethal US targeting assignments and their predicted effect on the local population in the counterinsurgency in Afghanistan. Lastly, it presents an optimization-based method of nonlethal target assignment selection. Our main experimental result is that the optimization-based assignments of US forces to local leaders on large networks achieved statistically significant higher arithmetic means of expected long-term attitudes than the doctrinal-based strategy.

1.6 Thesis Organization

In Chapter 2, we provide an operational overview of the struggle for popular support in counterinsurgencies. We describe the nature of insurgencies and how counterinsurgents, in particular the US Army, plan and conduct operations to defeat them. We also provide a functional decomposition of the nonlethal targeting process, the method by which US Army units identify, prioritize, and synchronize efforts to co-opt or otherwise gain support of individuals in order to win popular support. Lastly, in this chapter, we discuss the difficulties of performing the nonlethal targeting in the counterinsurgency campaign in Afghanistan.

In Chapter 3, we present our modeling approach to assist US Army units with nonlethal targeting. We present a detailed description of the models we formulated to represent social influences between Afghan local leaders, as well as approximate the social network in which these local leaders interact. This chapter also includes a detailed description of the mathematical model we used to determine the most beneficial US nonlethal targeting assignments.

In Chapter 4, we describe our implementation of the models as well as the three experiments we conducted to test the performance of our optimization formulation. We present analysis on the model's runtimes, performance compared to optimality, and operational performance against doctrine.

In Chapter 5, we identify specific areas for future research and offer insights as to how our work might be integrated into the current US Army targeting process.

In Chapter 6, we review the nonlethal targeting problem, summarize the work presented, and offer some conclusions.

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2 The Struggle for Popular Support in a Counterinsurgency

This chapter provides an overview of population-centric insurgency and counterinsurgency and a more detailed view of the conflict in Afghanistan.

2.1 Popular Support in Insurgencies and Counterinsurgencies

In conventional land warfare, armies fight in major engagements to destroy the opposing force and control physical terrain on the battlefield. In stark contrast, in irregular warfare and its two major forms, insurgency and counterinsurgency, each side fights for the political support of the population [9]. The people, as opposed to the terrain, are now the battlefield ([10], [11]). It is precisely this objective that makes insurgencies and counterinsurgencies so complex.

Formally, an insurgency is defined as an "organized movement aimed at the overthrow of a constituted government through the use of subversion and armed conflict" [12]. It is also known as a "protracted politico-military struggle designed to weaken the control and legitimacy of an established government, occupying power, or other political authority while increasing insurgent control" [2]. Insurgents essentially attempt to persuade the population, through a variety of strategies, to support or otherwise acquiesce to the insurgents' goals or force a political change.

A counterinsurgency (COIN) is defined as the "military, paramilitary, political, economic, psychological, and civic actions taken by a government to defeat an insurgency" [2]. In this subset of warfare, the Host Nation security forces and partners "operate to defeat armed resistance, reduce passive opposition, and establish or reestablish the legitimacy of the Host Nation's government" [9]. The end goals for the counterinsurgent are to demonstrate the strength of the Host Nation government in providing for the physical and security needs of the people, and for the people to consent to the government's rule.

In an insurgency/counterinsurgency conflict, each side's objective is the popular support of the people [13]. Each side must make its case to the people and struggle for the legitimate authority among them.

2.1.1 Defining Popular Support

While there is consensus in the notion that popular support is critically important in both insurgencies and counterinsurgencies, much less agreement exists on how to define popular

support ([13], [10]) and correspondingly how to conceptualize it in a way that is measurable and prescriptive (i.e., points to specific actions to achieve it). The disagreement, well discussed in *The Logic of Violence in Civil War* by Kalyvas, lies in viewing popular support as either 1) a confluence of attitudes, preferences, and allegiances, or 2) a set of observable behaviors [13]. One may think that a person who possesses the former would naturally exhibit the latter, and conversely one who exhibits the latter also possesses the former. In fact, researchers have shown that neither necessarily follows in the context of civil wars [13]. What one feels and what one does can be quite different due what Kalyvas describes as,

> variable and complex sets of heterogeneous and interacting motivations, which are affected by preferences over outcomes, beliefs about outcomes, the behavior of others and the networks into which people are embedded, and security considerations ([13]: 95).

Compounding the problem is that genuine behaviors and attitudes are both difficult to detect and measure by the counterinsurgent. While Kalyvas states that ultimately both the insurgent and counterinsurgent want a credible commitment of the people, irrespective of motivations [13], there is reason to believe that "attitudes inform decision-making processes and shape popular thinking on the legitimacy of the actions in the conflict" [2]. In the end, this author subscribes to the latter view that the counterinsurgent needs to influence attitudes in order to bring about the desired behaviors.

2.1.2 Forms of Popular Support

Studies have shown in an insurgency there is a range of popular support for or against either side with a significant portion of the population that is indifferent ([3], [13]). This concept is best depicted in Figure 2-1 from Army FM 3-24.2. Each component of the spectrum is explained in more detail below.

- *Active Support.* Active supporters are those who personally or publically align with either side. They view their side as the legitimate authority. Behaviorally, active supporters of insurgents may join the insurgent group, provide logistical or financial support, provide intelligence, provide sanctuaries, provide medical assistance, or provide transportation [2]. Active supporters of the government may join the army or police, take a government job, provide quality intelligence to the counterinsurgents, or make public statements denouncing the insurgents [10].

- *Passive Support.* Passive supporters are those who are lukewarm in their designation of a side in the conflict. They are often partial to one side only due to their acquiescence and who may be in closest proximity, rather than an overt or committed decision. Behaviorally, passive supporters of the insurgency are those who allow insurgents to conduct activities in their areas, or do not provide information to the counterinsurgents [2]. Passive supporters of the government may acquiesce or submit to the counterinsurgents, or support government operations if there is minimal risk [10].
- *Indifferent.* The indifference in a significant portion of the population is due to a survival instinct and perhaps opportunism [13]. Indeed, when the population is caught in the middle between two armed actors, there may be a tendency for the people to either 1) cater to whomever is immediately present at the time, or 2) remain neutral until there is clearly a victor.

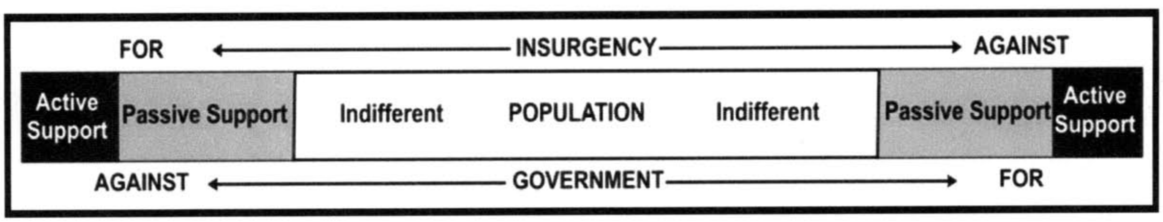

Figure 2-1: Range of Popular Support [3]

2.1.3 Moving Along a Spectrum of Support

A significant complexity is that the population can shift its allegiances (i.e. move along the spectrum) repeatedly throughout the conflict ([14], [13]). The vast majority of the population caught in the middle is not comprised of ideologues that stubbornly support one side or the other. Rather, they are people who make rational decisions of allegiance based upon the signals that they receive at anytime during the conflict and which can lead them to shift one way or the other. Some of the important signals include 1) who can protect them, 2) who can best provide for them, and 3) who will ultimately win [15].

2.2 Operational Environment (OE) in a Counterinsurgency

Army Field Manual 3-0 defines the operational environment as "a composite of the conditions, circumstances, and influences that affect the employment of capabilities and bear on the decisions of the commander" ([9]: 1-1). The US Army has developed a systematic approach to conceptualizing the operational environment in a counterinsurgency, which we highlight here. The bottom line is that the operational environment in COIN is very complex and that the US

Army believes units must understand all the pertinent variables and considerations when trying to gain support of the population.

2.2.1 Operational and Mission Variables

The US Army uses eight operational variables (PMESII-PT) to assist it in analyzing the OE. They are:

- *Political.* The distribution of power and authority at all levels of government, including formal and informal political systems.
- *Military.* The capabilities of the fighting force in all forms: Host Nation, allies, militias, etc.
- *Economic.* The broad categories of the economy in the particular area.
- *Social.* The characteristics of all societies and groups in the particular area.
- *Information.* The study of how information is collected, disseminated, as well as possibly manipulated.
- *Infrastructure.* The basic capabilities and assets of a functional society.
- *Physical Environment.* The terrain and its impact on all sides of the conflict.
- *Time.* This is how time affects all sides of the conflict [3].

In addition to the operational variables, the US Army also analyzes its mission in the context of the OE with the mission variables (METT-TC). They are:

- *Mission.* The unit's task and purpose.
- *Enemy.* An analysis of the enemy's disposition, composition, strengths, weaknesses, as well as the five elements of the insurgency—leaders, guerillas, auxiliary, underground, and mass base (explained in more detail in section 2.3.1).
- *Terrain and Weather.* An analysis of natural features and their effects on operations.
- *Troops and Support Available.* An analysis of the number of soldiers (from the allies and Host Nation government) available to participate in the mission and their specific skills and capabilities.
- *Time Available.* The analysis of the time frames (short, medium, and long term) in which the mission is conducted.
- *Civil Considerations.* This is often the most important mission variable in COIN and one which we will explain in more detail below [3].

Area	*Structure*	*Capabilities*	*Organization*	*People*	*Events*
Tribe	Cemeteries	Sewer	Tribal	Phones	Weddings
Families/Clans	Religious shrines	Water	Family/clan	Speeches	Birthdays
Ethnicity	Houses of worship	Electrical	Religious	Face-to-face meetings	Religious gatherings
Religion	Bars/tea shops	Academic	Ethnic	Media/radio	Funerals
Economic districts	Social gathering places	Trash	US/coalition forces	Media/TV	Major religious events
Smuggling routes	Print shops	Medical	Governmental agencies	Media/print (newspaper)	Anniversaries of wars or battles
National	Internet cafes	Security	Farmers or Unions	Visual (graffiti, signs)	Holidays
Social classes	Television	Market (use and goods)	Community	Visual (videos, DVDs)	Harvests
Political districts	Radio station	Employment and commerce	Military or militia units	Audio (pirated or illegal radio)	Reconstruction openings
Military districts	Hospitals	Crime and justice	Illicit organizations	Rallies or demonstrations	Town or council meetings
School districts	Banks	Basic needs	Insurgent groups	Restaurants	Elections
Road system	Dams	Public health	Gangs	Door-to-door	Sports events
Water sources	Bridges	Economic (jobs)	Businesses organizations	Internet	
Water coverage	Police stations	Religion	Police	Markets	
Water districts	Gas stations	Displaced persons and refugees	Nomads	Sports	
Construction sites	Military barracks	Political voice	Displaced persons and refugees	Religious gatherings	
Gang territory	Jails	Civil rights, individual rights	Volunteer groups	Parks	
Safe areas/ sanctuary	Water pumping stations		Intergovernmental organizations	Family gatherings	
Trade routes	Oil/gas pipelines		Political	Gas lines	
Power grids	Water lines		Contractors	Bars/tea shops	
	Power lines		NGOs	Food lines	
	Storage facilities		Labor unions	Job lines	

Figure 2-2: Example Considerations within each ASCOPE category [3]

2.2.2 Criticality of Civil Considerations

Because popular support is the main objective in the insurgency/counterinsurgency conflict, understanding the civilian considerations is paramount [3]. A list of typical civilian considerations from FM 3-24.2 is shown in Figure 2-2 [3]. The considerations are organized into the major categories: area, structure, capabilities, organization, people, and events (ASCOPE). We describe each category in more detail below:

- *Area.* This category entails the specific localities of a unit's assigned area of operations (AO). It includes physical components of the terrain that may affect the population, but also some less obvious or visible boundaries like ethnic, tribal, or economic lines.
- *Structure.* This category includes the physical objects and buildings in the AO that may be important to the infrastructure and community.
- *Capabilities.* This category includes all the available means for the government to provide goods, services, and civil stability to its people.
- *Organization.* This refers to the nonmilitary groups or institutions in the AO. The segmentation of society can be very diverse, and each group will have its own interests and activities.
- *People (Means of Communication).* This encompasses all the various ways in which the people may communicate in the AO, both formally and informally, as well as the locations in which that communication occurs. All groups and subgroups should be considered. This category also includes the avenues of mass communication, but also interpersonal communication and influence.
- *Events.* This category includes all significant occurrences in the AO, both public and private. The events could be a single-occurrence or happen cyclically or routinely.

There are numerous considerations when dealing with a population, and understanding all of them is critical to the long-term success of the insurgent or counterinsurgent [3].

2.3 Insurgency

In this section, we explore the aspects of insurgencies that are most pertinent to how the insurgents gain popular support.

2.3.1 Generic Organization

An insurgency has three components [3]:

- *Elements.* Elements of an insurgency consist of leaders, guerillas (lower-level fighters), underground (cellular organization of active supporters), auxiliaries (sympathizers with a logistical role), and mass base (passive supporters).
- *Dynamics.* The dynamics of an insurgency are leadership, objectives, ideology, environment and geography, external support, internal support, phasing and timing, and organizational and operational patterns.
- *Strategies.* The six common insurgent strategies are urban, military-focused, protracted popular war, identity-focused, conspiratorial, and composite and coalition.

Indeed volumes have and can be written about insurgent dynamics and strategies. In this work, we will focus primarily on the *dynamics* component of an insurgency, in particular internal support, and insurgent activities that generate it.

Internal support is defined as any support provided from within the country and has two general categories: popular support and logistical support. In order for an insurgency to survive or succeed, it must have both. Strong internal support is often provided by the *mass base* element of the insurgency. This mass base permits or encourages the insurgents to operate in areas and may even provide food and shelter for them [13].

2.3.2 Mechanisms of Mobilization

The specific methods that insurgents use to mobilize supporters or otherwise achieve acquiescence from the population are:

- *Persuasion.* This is use of political, social, religious, security, or economic factors to convince a person to support one side or the other.
- *Coercion.* This is the use of violence or threats of violence to forcibly gain support of a person [13].
- *Reaction to abuses.* This method involves the insurgents instigating indiscriminate violence by the counterinsurgent or propagandizing the actions of a harsh or corrupt government. The result is the alienation of people away from the counterinsurgent and toward the insurgents.
- *Foreign support.* This is the involvement of a foreign government to finance, lend legitimacy to, or otherwise foment an insurgency.
- *Apolitical motivations.* This is the involvement in the insurgency of foreign volunteers, criminals, and mercenaries whose motivations are often money or extremism rather than politics [3].

2.4 Counterinsurgency

In this section, we explore the pertinent aspects of US COIN doctrine, and how the military plans and conducts COIN operations in order to gain support of the population.

2.4.1 Full Spectrum Operations

COIN is the simultaneous and continuous combination of the three types of operations: offense, defense, and stability operations.

- *Offense.* These are "combat operations conducted to defeat and destroy enemy forces and seize terrain, resources and population centers" [9]. Offensive operations disrupt the insurgent's ability to establish bases and consolidate forces.
- *Defense.* These are "combat operations conducted to defeat an enemy attack, gain time, economize forces, and develop conditions favorable for offensive or stability operations" [9]. Defensive operations protect and secure areas from insurgents.
- *Stability.* These are operations that "encompass various military missions, tasks, and activities conducted outside the United States in coordination with other instruments of national power to maintain or reestablish a safe and secure environment, provide essential government services, emergency infrastructure reconstruction, and humanitarian relief" [9]. Stability operations frustrate insurgent attempts to disrupt people's lives and/or prevent their achieving support by effectively addressing population grievances.

Because the main objective is winning the support of the population, stability operations often have more relevance and importance in COIN than the other types of operations [9]. Eliminating insurgents, while sometimes necessary, is also more often detrimental to the cause by making more enemies or generating grievances from the population. The strategy is a significant mindset shift from conventional warfare where destroying enough of the enemy's forces is sufficient.

2.4.2 Lines of Effort (LOEs)

Doctrinally, US Army units utilize lines of effort (LOEs) to plan, direct, and allocate resources to operations. For a counterinsurgency, there are seven LOEs that essentially constitute a prescription for countering the insurgent strategy, for establishing legitimacy of the Host Nation government, and for winning the political support of the people [3]. Figure 2-3 is a graphic from FM 3-24.2 that depicts how operating along the counterinsurgency LOEs are designed to

increase the proportion of the pro-government population while simultaneously decreasing both the proportion of the pro-insurgent and neutral populations. Below is a more detailed description of each LOE.

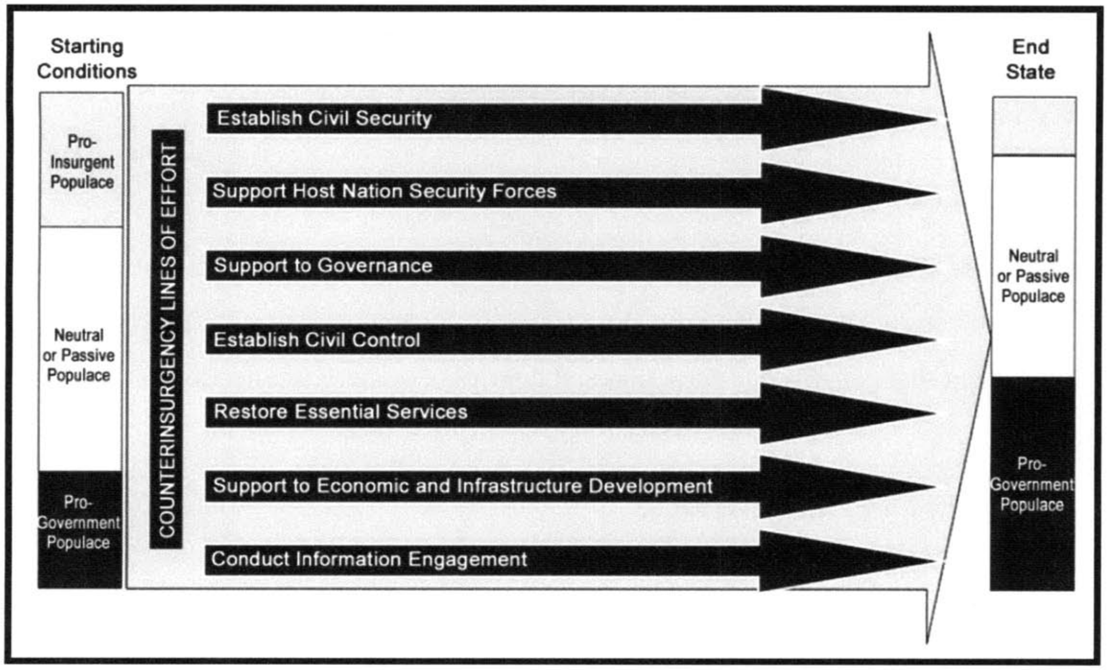

Figure 2-3: Counterinsurgency Lines of Effort [3]

2.4.2.1 Establish Civil Security

This line of effort calls for the protection of areas, resources, and people from internal and external threats. Civil security is a fundamental need before a society and government can function adequately. US COIN doctrine recognizes that this LOE is only a temporary but often necessary effort until the Host Nation can sufficiently protect its citizens from threats. Missions in this LOE may include:

- Securing designated facilities and population centers.
- Conducting area security (patrols to disrupt insurgent bases and sanctuaries)
- Defeating insurgent forces [2].

2.4.2.2 Support Host Nation Security Forces

This line of effort involves training and building a dependable military and police force to protect the people. In order for the Host Nation government to be recognized as a legitimate

authority, it must be able to provide security for its people. Missions for the US and allies in this LOE may include:

- Establishing mobile training teams and providing advisers to work with the Host Nation security forces.
- Establishing military and police academies.
- Conducting joint operations with Host Nation security forces [2].

2.4.2.3 Support to Governance

This line of effort involves the development and improvement of government institutions. Insurgencies gain strength only when the Host Nation government is weak. Therefore, a strong stable government that can provide direction and control of society is a necessity. Efforts along this line include:

- Developing effective local governance.
- Supporting anti-corruption initiatives [3].
- Providing public administration.
- Keeping property and other public records.
- Establishing a public finance and taxation system [2].

2.4.2.4 Establish Civil Control

This line of effort builds or preserves the institutions, such as the judiciary and law enforcement, within society that governs individual and group behavior. Efforts along this line include:

- Establishing and enforcing rule of law.
- Establishing public order and safety.
- Establishing a corrections system [3].

2.4.2.5 Restore Essential Services

This line of effort provides for a population's life support to include water, electricity, and sewage. People expect their government to be able to provide these basics. As with establishing civil security, US and allied efforts along this LOE are considered provisional until the Host Nation government and other interagency organizations can provide these services. Activities along this LOE include:

- Conducting assessments to establish needs and priorities for services.
- Partnering and planning with interagency organizations to restore services.
- Recognizing local sensitivities and employ as much local leadership, talent, and labor as possible [2].

2.4.2.6 Support to Economic and Infrastructure Development

This line of effort includes the short- and long-term activities that reestablishes an economy and stimulates sustainable economic activity. An area's stability is closely related to the population's economic situation. Efforts include:

- Working with Host Nation government to reduce unemployment.
- Creating a secure environment where businesses can thrive.
- Being astute when giving out contracts for work and be sensitive to tribal or clan networks [2].

2.4.2.7 Conduct Information Engagement

This line of effort involves informing and influencing the population by messages and actions to gain political support for the government. It is a critical component of the counterinsurgency LOEs. This effort includes:

- Broadcasting supportive themes and messages on all available media: radio, TV, newspapers, flyers, billboards, and the Internet.
- Providing truthful accounts quickly and accurately to the public in order to counter insurgent propaganda.
- Managing local expectations.
- Conducting all operations in a firm, fair, and professional manner, and in a manner respectful of the population's cultures and values [2].

2.4.3 Planning Processes

The US Army utilizes several processes to plan and execute operations. For tactical-level planning, it utilizes the military decision making process (MDMP) and one of its sub-processes called the intelligence preparation of the battlefield (IPB). For tactical-level synchronization of planning as well as for preparation and mission execution, the Army uses the targeting process. Figure 2-4 depicts how all these processes fit together. We discuss what comprises each process in the following subsections.

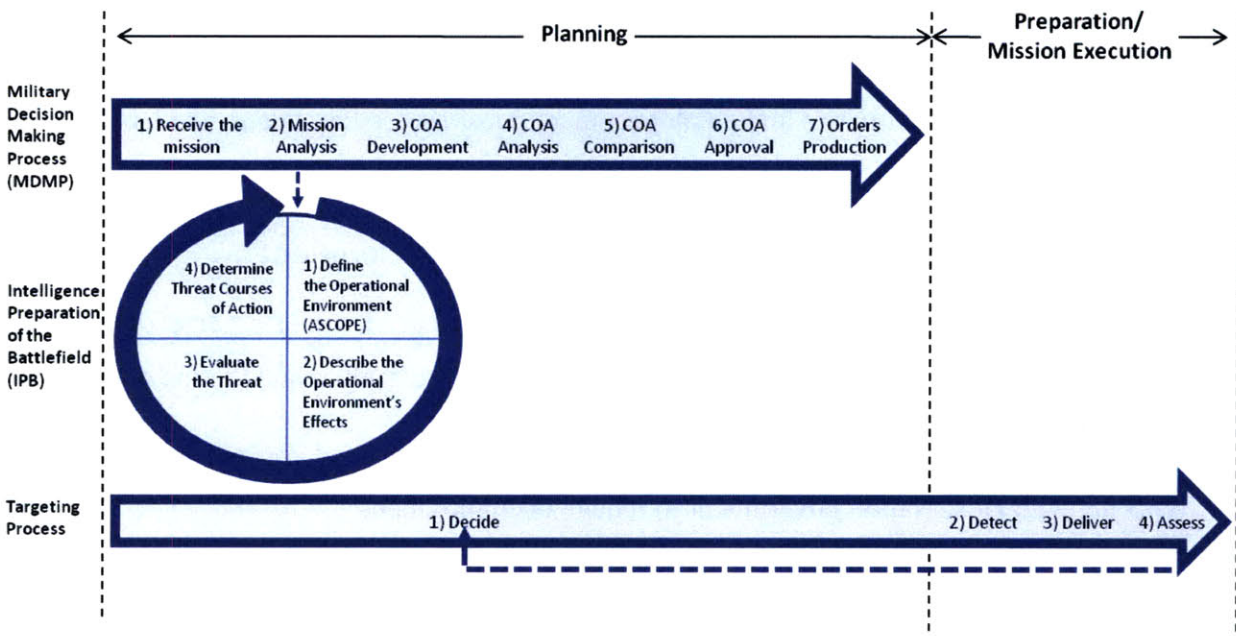

Figure 2-4: Army Planning Processes Synchronization

2.4.3.1 Military Decision Making Process (MDMP)

Executing military operations, especially COIN, is a very complex activity. It demands a comprehensive, logical process that considers all factors pertinent to the operation, generates and analyzes a set of possible options, and methodically selects the best option. This formal process is known as the military decision making process (MDMP) and is used by US Army units with staffs (battalion-level or above) to plan operations and prepare orders [16]. MDMP also synchronizes the commander and the staff in the planning process.

The process is conducted in seven steps, broadly explained below, but explained in further detail in Army FM 5-0 [16].

- *Receive the Mission (Step 1).* The unit gets the mission in the form of an operations order (OPORD) from a higher headquarters.
- *Mission Analysis (Step 2).* Staff officers analyze the mission received by identifying specified and implied tasks, any constraints of the mission, and limitations of the unit's capabilities. It is in this step as well that the intelligence officer leads the analysis of the enemy, environment, and terrain called the Intelligence Preparation of the Battlefield (IPB). This process is explained in more detail in Section 2.4.3.2.
- *Course of Action Development (Step 3).* After the staff thoroughly comprehends the mission, staff officers then develop several plans (called courses of action or COAs) which can

accomplish the mission. Each COA must meet the criteria of suitability, feasibility, and acceptability. The staff briefs the COAs to the commander, who gives appropriate guidance and approves them for further analysis.

- *Course of Action Analysis-War Game (Step 4).* The staff conducts a war game of each COA as it relates to the enemy and friendly missions. They record anticipated shortfalls and adjustments, and adjust the COA appropriately.
- *Course of Action Comparison (Step 5).* The staff establishes certain criteria with which to measure each COA, and conduct a comparative analysis.
- *Course of Action Approval (Step 6).* The staff briefs the results of the war game, COA comparison, and a recommended COA to the commander. The commander can select one, none, or piece together an alternative COA with the available information and analysis.
- *Orders Production (Step 7).* With an approved COA, the staff begins generating the OPORD to issue to subordinate units and directing them with the mission and tasks assigned.

2.4.3.2 IBP

As part of the mission analysis step in MDMP, US Army units also conduct a thorough analysis of the threat and the operational environment in a sub-process called the intelligence preparation of the battlefield (IPB). Once initiated in step 2 of MDMP, the staff conducts IPB continuously with updated information and staff estimates. The cyclic nature of the IPB process is depicted in Figure 2-5.

Intelligence is vitally important in military operations, but especially in COIN. Because success in COIN depends on the ability of the counterinsurgent to win support from the population over the insurgent, intelligence in understanding the population is critical. Therefore IPB conducted in COIN places a heavier emphasis on civil considerations as opposed to IPB in other military operations [2].

IPB as it pertains to COIN contains the following steps:

- *Define the Operational Environment (Step 1).* This step involves establishing an area of interest and influence based on terrain, infrastructure, and the population. This step also involves a thorough analysis of all the operational variables (PMESII-PT) and the mission variables (METT-TC). An in-depth examination of the civilian considerations also requires assessing ASCOPE. Upon completion of this step, military planners and commanders are able to identify all the salient aspects of the operational environment.

- *Describe the Operational Environment's Effects (Step 2).* This step involves synthesizing and understanding the information from step one, and determining the impacts and significance of the aspects identified. In addition, this step identifies the root causes for the insurgency and why the population would be drawn to support it.
- *Evaluate the Threat (Step 3).* This step involves thoroughly examining the enemy composition, capabilities, methodologies, and vulnerabilities.
- *Determine Threat Courses of Action (Step 4).* Finally, this step involves determining what are the enemy's likely courses of action by synthesizing how the enemy uses the aspects of the OE and their effects to influence the population to support the insurgency (determined in steps 1 and 2) and understanding their ability to carry it out (determined in step 3) [17].

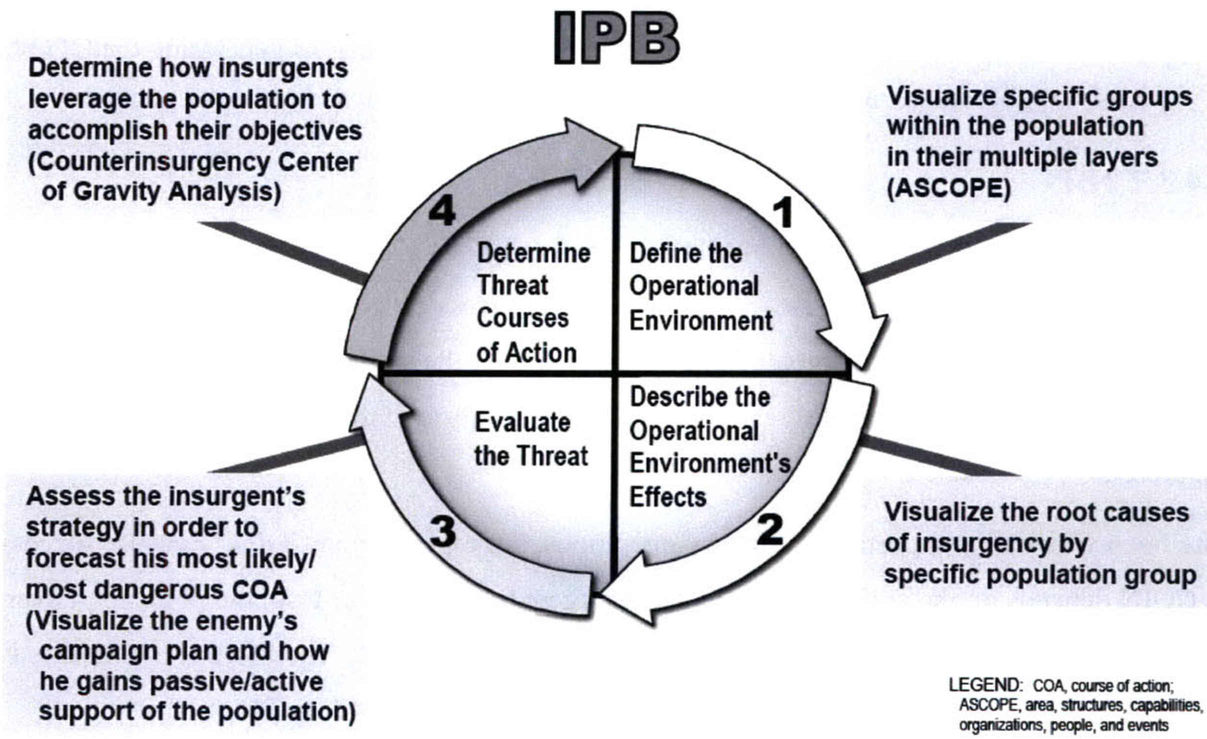

Figure 2-5: Intelligence Preparation of the Battlefield [17]

2.4.3.3 Targeting

In addition to MDMP and IPB planning processes, the US Army also utilizes the targeting process in COIN to focus the commanders and staff on identifying, prioritizing, and engaging (lethally and non-lethally) personalities or areas to accomplish the mission. Targeting encompasses the range of military activities from planning to preparation and execution. Lethal targeting is attacking while nonlethal targeting is influencing. The targeted personalities or areas can be either enemy or neutral. The process also considers the synchronization of the targeting

over time and space [18]. This work only concerns nonlethal targeting in support COIN. It is accomplished in a cycle of four functions:

- *Decide.* This function involves the identification and prioritization of "individuals or groups to engage as potential counterinsurgency supporters, [and] targets to isolate from the population" [3]. This function also includes a decision on how the target is to be engaged (through what means and methods). It occurs concurrently with the planning process (MDMP).
- *Detect.* This function involves the effort to locate the target using a variety of capabilities available to the US Army, including human intelligence (HUMINT) and soldiers on patrol. For example, nonlethal targets may be detected through frequent reconnaissance patrols to a leader's home to determine his/her presence, or through attendance at meetings to greet the leader. This function occurs during the preparation and execution.
- *Deliver.* This function involves the execution of the engagement in accordance with the 'how' determined in the Decide function. For example, nonlethal targets are engaged when information engagement is used to influence a local leader to support the counterinsurgents or when a reconstruction project is initiated that earns favor from the population [3]. This function also occurs during the preparation and execution.
- *Assess.* This function gives commanders an understanding on the effects of the potential actions and actions taken on a target. Targets may be reengaged until the desired effect is achieved or may be abandoned for another target depending on the results of this assessment [18]. This function occurs throughout the entire process, but is most focused during and immediately following execution.

Figure 2-6 from FM 3-24.2 lists some common targets (both lethal and nonlethal) chosen in COIN. Given that nonlethal targeting is so important to COIN, we discuss it in more detail in the following section.

Personality Targets

- Lethal
  - Insurgent leaders to be captured or killed
  - Guerillas
  - Underground members
- Nonlethal
  - People such as community leaders and those insurgents who should be engaged through outreach, negotiations, meetings, and other interaction
  - Insurgent leaders
  - Corrupt host-nation leaders who may have to be replaced

Area Targets

- Lethal
  - Insurgent bases or caches
  - Smuggling routes
- Lethal and Nonlethal Mix
  - Populated areas where insurgents commonly operate
  - Populated areas controlled by insurgents where the presence of U.S. or host-nation personnel providing security could undermine support to insurgents
- Nonlethal
  - Areas lacking essential services (SWEAT-MSO) that support the government

Figure 2-6: Lethal and Nonlethal Targets in COIN [3]

2.5 Nonlethal Targeting in a Counterinsurgency

Nonlethal targeting is a critical activity in COIN. With the ultimate goal of winning the support of the population, the use of nonlethal force may often be more effective than lethal force. Indiscriminate violence or even targeted lethal operations will likely engender increased resentment and bolster a known insurgent method of recruitment and mobilization ([3], [15]). As a process, nonlethal targeting is important because it helps units identify, prioritize, synchronize, and appropriately engage targets. Units conducting a counterinsurgency have a tremendous number of people from which to potentially garner support. Determining who may be the most effective in gaining the support of a particular group or eliciting a specific behavior from them is often difficult. Meanwhile, the same unit is often constrained in a variety of resources used to conduct nonlethal targeting, including personnel, time, development money, equipment, as well as ability to provide security and protection. In this chapter, we describe the nonlethal targeting process in greater detail as well as its associated difficulties in COIN.

2.5.1 Targets and Nonlethal Activities

A target, according to FM 1-02, is an "area, complex, installation, force, equipment, capability, function, or behavior identified for possible action to support the commander's objectives, guidance and intent" ([19]: 1-184). The definition is broad enough to include people (as a force), and a person's sphere of influence (as an area). Figure 2-6 lists some frequently considered nonlethal targets. Sometimes, the term "target set" is used to denote a class or type of person, whereas the term "target" refers to a specific individual within that target set.

Additionally, a nonlethal activity (the field manual uses the term 'nonlethal fires') is any method of engagement that does not "directly seek the physical destruction of the intended target and are designed to impair, disrupt, or delay the performance of enemy operational forces, functions, and facilities" ([19]: 1-133). The term once again is broadly defined, and can encompass a myriad of tasks. If one considers that a population favorable to the insurgents can provide them with intelligence, sanctuary, and food, then that same population is certainly considered a legitimate nonlethal target. To the counterinsurgent, the target is the population, and the desired effects are for them to be supportive of COIN operations and to accept the legitimacy of the Host Nation government. Common nonlethal activities that may achieve this desired effect include:

- *Meetings (public or private).* Meetings, sometimes referred to as engagements, are a common form of nonlethal activity in COIN. They facilitate communication between the counterinsurgent and a person or a group of people who might have influence over a segment of the population. Depending on the culture, counterinsurgents might only be successful in engendering support after a series of private meetings, the early ones of which can involve a significant amount of socialization and trust-building [20]. At these meetings, both the counterinsurgent and the targeted person(s) may request specific assurances or items from the other. A public meeting, like a town hall, is another form of engagement usually used to disseminate information and convey messages to the population in a more personal manner than using mass media [3].
- *Aid and assistance missions.* This activity involves a demonstration of goodwill and the distribution of aid to a particular town or village with the purpose of co-opting the population or perhaps just one person. The assistance may be medical, veterinarian, educational (school supplies), or subsistence (food and clothing). Similar to the well-digging example in Section 2.6.4, how the counterinsurgent delivers the aid can have as much of a nonlethal effect as the aid itself. On one hand, a unit may give the aid out in a mass gathering, not realizing that it

could be undercutting the authority of local leaders to provide for their people. On the other hand, a unit may give the aid to one particular person to distribute, thereby intentionally or unintentionally distinguishing him above others.

- *Reconstruction projects and economic stimuli.* Another nonlethal activity in COIN is providing reconstruction projects while simultaneously stimulating the local economy with jobs. To engender the support of a key leader or the entire village, a counterinsurgent may start a project in a village and accept a contract from a reconstruction firm that uses local labor.
- *Bestowing legitimate or perceived authority.* Similar to the effect of aid delivery missions, a counterinsurgent may bestow some real or perceived authority on a person by publically praising him or being deferential to his wishes. For example, a counterinsurgent may refrain from conducting night raids in a particular village after a request from the village elder.
- *Providing security or protection from reprisals.* Because of the insurgent's threat of violence (as explained in Section 2.6.2.2), a significant nonlethal activity is providing protection for an important person who actively supports the government. This could be in the form of training and providing equipment to his bodyguards or even the counterinsurgents providing security directly [21].
- *Providing support or training to militias and paramilitary forces.* In an effort to empower a local authority to take charge of the security of his people against the insurgents, the counterinsurgent can deputize an existing militia, or hire and train local villagers to serve as an auxiliary police force. Often easier prescribed than done, it is important in this particular effort to always make provisions to ensure that a militia leader's power never exceeds that of the government [3].

2.5.2 Functional Decomposition of Nonlethal Targeting Activities

In this section, we describe in detail each of the steps of nonlethal targeting as executed by a battalion headquarters. It is worth noting that counterinsurgency is a unique form of warfare in which authority and responsibility are pushed down to lower units than in conventional warfare because of the need to work locally with the population. While doctrinally the targeting process is reserved for units with a full staff (battalions, brigades, and above), out of necessity a company in COIN may piece together a small section of soldiers to mimic the critical components of the targeting process ([22], [23]).

Each stage of the targeting process actually represents the preparedness of the unit to engage a particular target. Targets may be in different stages of the process and may complete a

‘lifecycle’ in different amounts of time (typically in weeks to months) [22]. The staff’s continuous challenge is to implement a management system that sorts out which targets are prepared for action at which stage, while ultimately working to accomplish the mission.

An additional challenge of the targeting process is that it includes both lethal and nonlethal targeting in the same functions. In the beginning of the process, the staff has the responsibility to decide which targets need to be eliminated (lethally) and which need to be engaged as potential supporters (nonlethally) [3]. The description of the targeting process that follows omits any reference to lethal targeting and assumes that the staff has already separated the targets into the appropriate categories.

Figure 2-7 depicts the four steps of nonlethal targeting with their associated inputs and outputs. The description of each step follows:

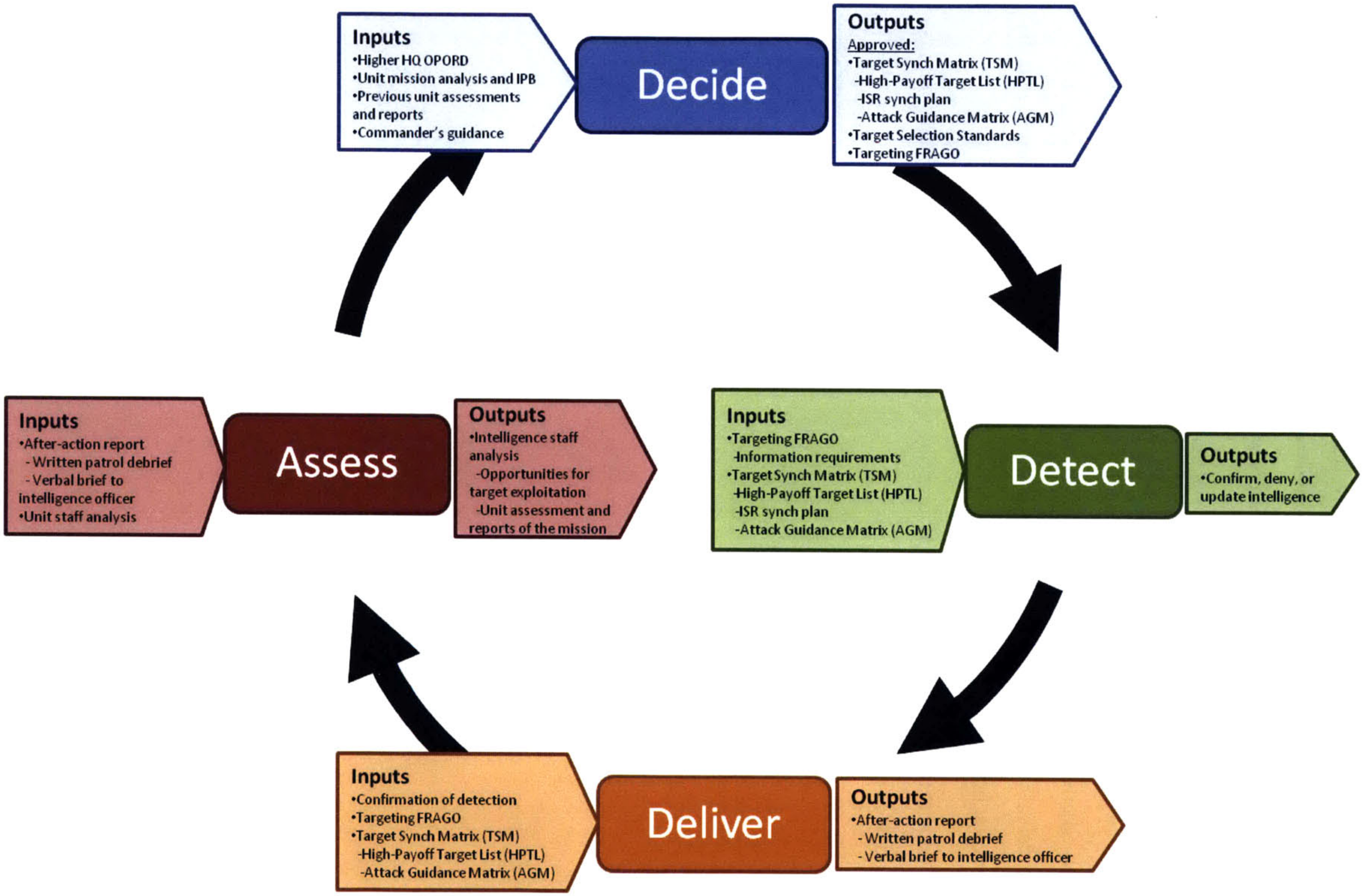

Figure 2-7: Nonlethal Targeting Functional Decomposition

The targeting process has an expanded role and applicability in COIN. Units with a counterinsurgency mission often face multiple objectives (such as influencing various people) that must be acted upon at different times within a specified period. These objectives present themselves more as a series of targets than something that can be fully predicted at the start of an operation [3]. The targeting process in COIN, however, is still fully integrated into MDMP ([3], [18]). Unless a unit changes areas of operations, it will likely conduct an initial MDMP and IPB (during which many base documents are produced), and afterward weekly, targeting-focused MDMPs to drive operations. All the base MDMP products are continuously refined and updated at each of the weekly MDMPs [3]. The targeting-focused MDMP concludes with the publishing of a weekly fragmentary order (FRAGO).

In the following sections, we describe in detail the four functions of nonlethal targeting as integrated into the weekly, targeting-focused MDMP process. We focus on the *Decide* function and its sub-processes because of their relevance to this work.

2.5.3 Decide

The nonlethal targeting process begins with the decide function, which occurs in a meeting called the targeting working group. This meeting, usually held weekly, is attended by the staff after the commander has issued some nonlethal targeting guidance. The four inputs into this function are 1) the higher headquarters' OPORD or FRAGO, 2) mission analysis and IPB products, 3) previous assessments and reports from subordinate units, and 4) commander's guidance. Each source may nominate potential nonlethal targets for the COIN mission. The higher headquarters' order will likely specify target sets in the short or long term. The IPB conducted by the battalion staff and based off of a thorough PMESII-PT and ASCOPE analysis will produce a high value target list (HVTL) of the local population. Previous reports (generated from a prior *Assess* phase) may suggest additional target sets or targets. And lastly, at any time, a commander may issue guidance that nominates some more target sets or specifies a desired effect on those target sets.

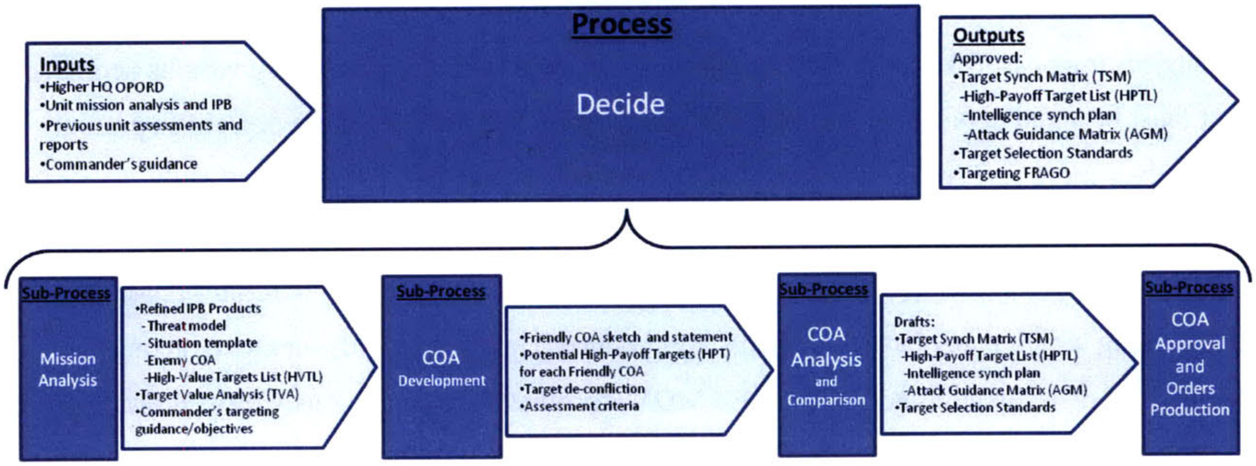

Figure 2-8: Decide Function

In the decide function, staff members at the targeting working group process the inputs using a targeting-focused MDMP to make decisions on the prioritization, synchronization, and means of targeting.

2.5.3.1 Sub-process 1: Mission Analysis

This sub-process is typically an abbreviated version of the base mission analysis (Step 1) conducted during the initial MDMP when the unit began COIN operations in a particular area. All the four inputs of the decide function feed into this sub-process and provide it additional targets to consider. The staff draws upon the previously produced IPB products (threat model, situation template, enemy COAs, and the HVTL) and carefully considers how the new targets might weaken the enemy. The staff briefs and presents the refined IPB products and the target value analysis to the commander, who in turn provides more specific targeting guidance. The target value analysis is an accounting of each potential target and how it enables enemy actions. The outputs of this sub-process are: 1) the refined IPB products, 2) a target value analysis, and 3) commander's additional targeting guidance [18].

2.5.3.2 Sub-process 2: COA Development

In this sub-process, the staff takes the outputs from the mission analysis sub-process and meets in another targeting working group to generate friendly COAs. After considering how each target can negatively affect the enemy, the staff decides what nonlethal actions can achieve that effect. Each COA is condensed into a readable format consisting of a sketch and mission statement.

Each COA will also contain the proposed *high payoff target list (HPTL)*, which is a list of prioritized lethal and nonlethal targets, organized by phase of the COA. Doctrinally, these targets are those "whose loss to an enemy will contribute to the success of the mission" ([3]: 4-30). Furthermore, the staff must also conduct target de-confliction, a step that ensures that within each COA, no person is redundantly targeted or subjected to engagements of mixed intentions. Finally, the staff must create assessment criteria, i.e., standards on measuring the success of the targeting action. The outputs are: 1) friendly COAs in a sketch and statement, 2) HPTL, 3) target de-confliction, and 4) assessment criteria [18].

2.5.3.3 Sub-process 3: COA Analysis and Comparison

In this sub-process the staff analyzes the proposed COAs and mentally plays a war game of each against the enemy. Based off of the IPB products (such as the enemy COAs and situation templates) the staff anticipates how their friendly COA will do against the enemy. After making any necessary refinements, the staff will compare the COAs and produce drafts of the following products in support of each COA [18]:

- *Intelligence Synchronization Plan*. This is a plan to coordinate the collection of intelligence by all assets at the unit's disposal or can request. There are a variety of assets used to collect intelligence, but the ones most often employed to nonlethal targeting are patrols and HUMINT. Each of the assets listed in this plan are tasked to answer specific questions for the unit (a list called information requirements) [3].
- *Target Selection Standards*. These are criteria that every target must meet before it can be acted upon by a unit. According to FM 3-24.2, the selection standards for nonlethal targets "may include background information on an individual, meetings he may attend, and known associates" ([3]: 4-30).
- *Attack Guidance Matrix (AGM)*. This document associates every approved target with a corresponding directive on how and when the action will take place. This document also lists the desired effect after the engagement [3].
- *Target Synchronization Matrix (TSM)*. This key document consolidates the information from the HPTL, intelligence synchronization plan, and the attack guidance matrix. In generic form, a TSM may be organized like Figure 2-9.

HPT #	Target Set	Target	Location	Intel Asset Synch		Engagement Guidance			
				Who Detects	When	Who Engages	When	How	Desired Effect

Figure 2-9: Generic Target Synchronization Matrix (TSM)

2.5.3.4 Sub-process 4: COA Approval and Orders Production

This is the final sub-process of the decide function. This function involves the brief of the previous draft versions of the targeting products for the commander's approval. The outputs of this function are commander-approved products listed below:

- *High-Payoff Target List (HPTL).*
- *Intelligence Synchronization Plan.*
- *Target Selection Standards.*
- *Attack Guidance Matrix (AGM).*
- *Target Synchronization Matrix (TSM).*
- *Targeting FRAGO.* This is the fragmentary order issued to subordinate companies that directs who, when, and how to target, and to what effect. Included in this order is the approved target synchronization matrix [18].

2.5.4 Detect

Detect is the second step in nonlethal targeting and involves all subordinate units and assets working to locate the HPTs so that they can be engaged. This entire step is driven by the intelligence synchronization plan (an output of the *Decide* step before) [3]. The inputs to this function are the TSM and the targeting FRAGO. The subordinate units receive these inputs and develop plans that accomplish the required tasks and answer the commander's information requirements. For example, the targeting FRAGO can direct a subordinate company to locate a particular local leader, coordinate a meeting with him to discuss the security needs of his people, and ascertain the leader's favorability of US forces. In this detection step, the commander then plans and executes a patrol or series of patrols to talk with the people to determine the physical

location of the leader. The output for this step is a confirmation of a location or disposition of a target that enables delivery of the nonlethal activity.

2.5.5 Deliver

Deliver is the third step in nonlethal targeting and is the execution of the plan developed in the *Decide* phase of the process [3]. The inputs include the confirmed detection from the previous step as well as the TSM and Targeting FRAGO. In this function, the designated unit or asset conducts the nonlethal activity, typically one of those listed in Section 2.5.1. In the previous example, this action may involve a unit leader conducting a follow-up meeting with the local leader and discussing security needs and both sides' desired behaviors. Depending on the nonlethal activity on a particular target, this step could take a significant amount of time. The only output in this step is an after-action report from the unit that conducted the activity. Often times, this report is a written patrol debrief, followed by a verbal brief of the results to the battalion intelligence officer.

2.5.6 Assess

The fourth and last step of the nonlethal targeting process is conducting the assessment of the activity and its effect on the target and the enemy. The inputs are the after-action report from the *Deliver* step as well as any unit analysis. The battalion staff then reviews these items, possibly receives more command guidance, and conducts their own analysis based on the assessment criteria developed in the *Decide* step. The analysis focuses on determining 1) the success of the activity in achieving the desired effect, 2) the need to repeat and if so, for how long, and 3) any exploitation targets that might have been discovered or gained in the process. The output of this step is an assessment and a report back into the targeting working group which may delete the particular HPT or re-nominate the target as a HVT.

2.6 Case Study: Taliban Insurgency in Afghanistan

While the US military has participated in a significant number of counterinsurgencies in the past, in this work we examine in depth the Taliban insurgency in Afghanistan, which continues to pose significant challenges today.

The US military and its allies have been operating in Afghanistan for over 8 years, since the invasion in late 2001 following the 9/11 attacks. The Taliban government in Afghanistan had provided a safe haven for terrorists who planned and conducted these attacks. The coalition achieved their first objective of toppling the Taliban regime relatively quickly. The second objective, to establish a stable democratic Afghan government, has been much more difficult. While there are many reasons for this difficulty, the primary one is the reorganization of the Taliban as a formidable insurgency. This section highlights the Taliban insurgency as a case study in the difficulties of gaining the support of the population.

2.6.1 Some Aspects of the Afghan Operational Environment

Volumes have been written on Afghanistan. This section merely presents some aspects of the operational environment in Afghanistan that is particularly relevant to this work. Specifically, we focus on the interrelatedness of the political, social, information, and physical environment operational variables, and how this interrelatedness leads to the emergence of influential local authorities among the Pasthuns, Afghanistan's largest ethnic group.

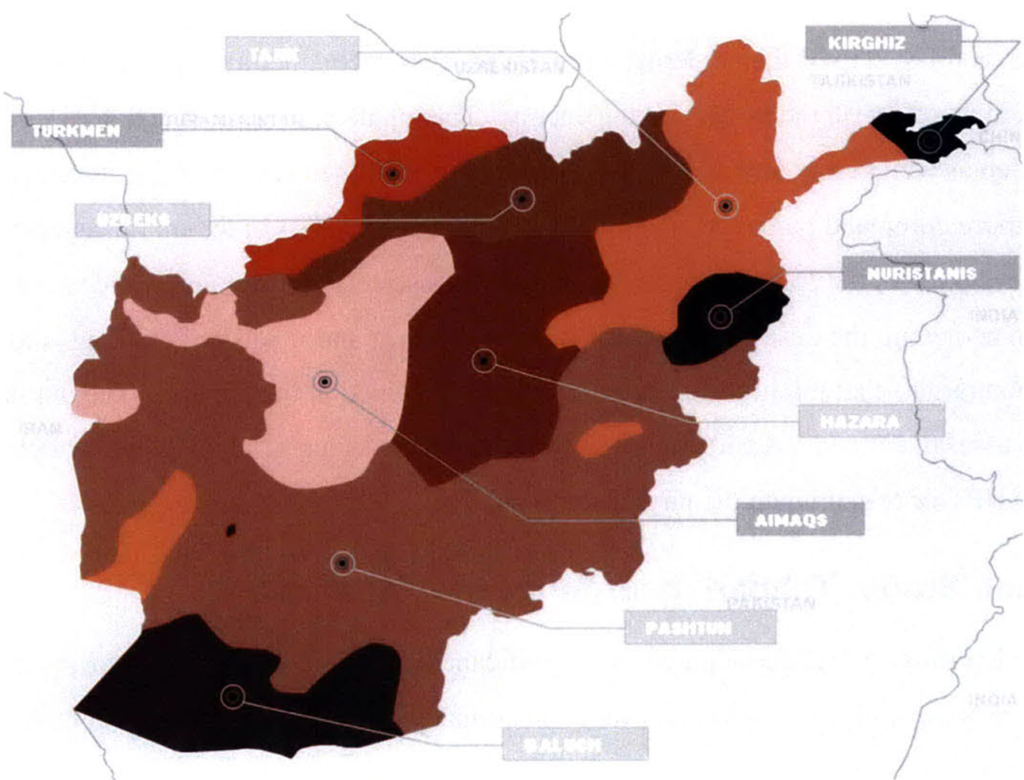

Figure 2-10: Ethnic Map of Afghanistan [24]

2.6.1.1 Pashtun Locality and the Terrain's Effect on Communication

While years of war have displaced many Afghans as refugees, Pashtuns are estimated to make up 42% of the country's population or about 11.9 million people [25] . Figure 2-10 depicts the Pashtun-dominated territories, mostly in the south and east, relative to other major ethnic groups in Afghanistan.

Approximately 70-77% of the Afghan population lives in rural areas [26]. We identify five levels of locality as: household, village, village cluster, district, and province. The household is the primary unit of locality [27]. Each household includes several generations of the extended family [27] totaling up to approximately 40 people all of whom live in the same 'compound' [28]. The oldest male or patriarch is often considered the head of household [27]. Multiple households together form a village. There may be between 100-200 households in a village, but the number can vary significantly. Villages that grow or are in close proximity to other villages may form a village cluster, which might share resources, representative councils, responsibility for security, or representation to the government [29]. Multiple villages form a district, which is a construct established by the Afghan central government. There are currently 398 recognized districts in Afghanistan, each headed by a sub-governor. Lastly, districts are grouped as provinces. There are 34 provinces in Afghanistan, each headed by a provincial governor appointed by Afghanistan's president.

2.6.1.2 Pashtun Social Structure

Ethnic Pashtuns have a traditional tribal structure, where membership is determined through patrilineal kinship. People identify first with a main tribe (from the earliest ancestor) but further sub-divide themselves into one of many sub-tribes (also known as clans or *khels*) [30]. Figure 2-11 depicts the five largest tribes of Pashtuns and the numerous sub-tribes associated with them. While tribes today give individual Pashtuns a group identity, they have questionable efficacy in organizing individuals to collective action [31].[2]

[2] Much of the decline in tribal importance can be attributed to the long Soviet-Afghan War as well as the subsequent civil war within Afghanistan. Three noticeable effects are the increased influence of fundamentalist mullahs, the marginalization of tribal authorities, and the rise in strength of warlords. The wars led many Afghans to flee as refugees to Pakistan. While there, entire generations of youth were raised in a non-tribal and religiously fundamental environment [49]. The Taliban, educated in *madrassas* (religious schools), had come to subscribe to Deobandi beliefs of Islamic fundamentalism and an intolerance of the modern practice of Islam. Following the war,

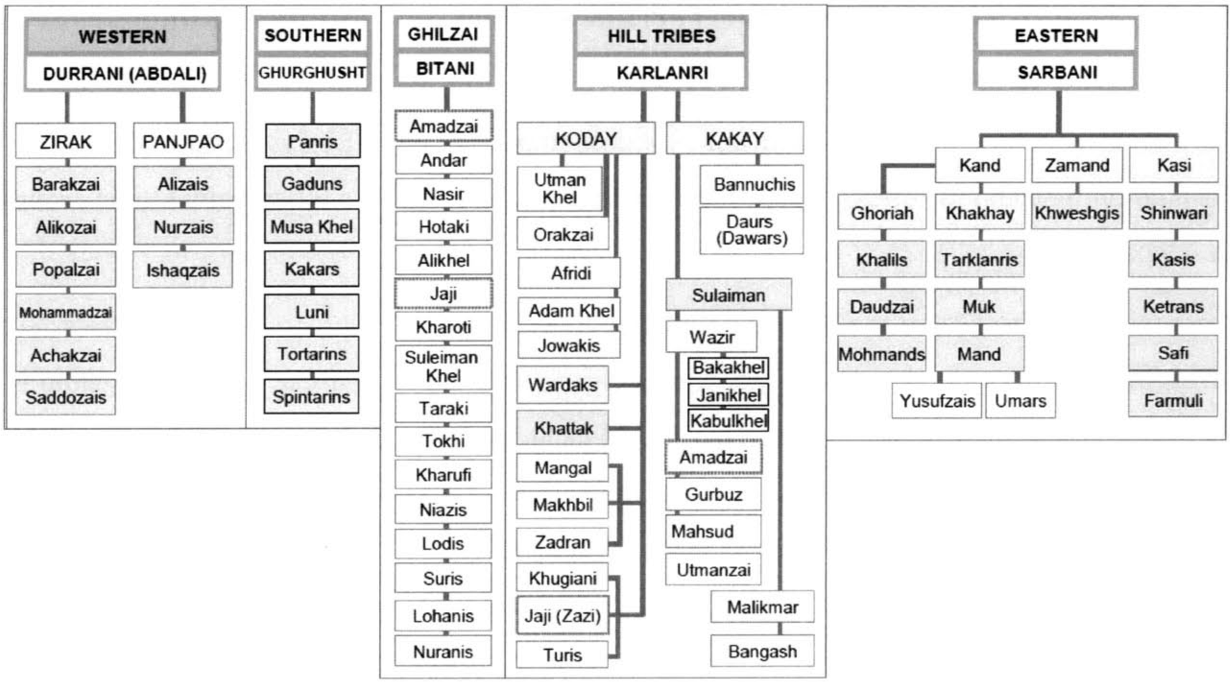

Figure 2-11: Pashtun Tribes and Sub-tribes [32]

Researchers have identified another construct called *qawm*[3] or solidarity group, which is an influential unit [31] of "political and community cognition" [33]. Every Afghan is a member of at least one *qawm* ([34], [35]) in which exists norms of solidarity [34] and loyalty [35]. Being of the same extended family, clan, village, region are common bases for membership ([31], [33], [34], [35]), but a *qawm* can also form on the basis of a shared political, social, economic, military, or cultural identity (all of which can cut across familial and tribal ties) [36]. For example, *qawms* can form among people who live in the same geographical area, are of the same profession, or follow the same leader for some political goal [31]. While knowing the *qawms* in a village or region may be extremely helpful, their varied basis for formation as well as their informality also make this knowledge precisely difficult to obtain. Additionally, rural Afghans identify more closely with their village *qawm* [37].

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both the ordinary people and the religious students returned to Afghanistan no longer adhering to a rigid tribal structure. In totality, there was a fracturing of traditional society. Tribal elders lost influence and were marginalized. Only the religious leaders, or *mullahs*, seemed to have the overarching influence from religion [49]. Additionally, the funneling of foreign aid and weapons to Afghans created warlords or local strongmen.

[3] *Qawm* is singular, and *aqwam* is the proper plural [35]. However, we will use *qawms* throughout this work for clarity.

In additional to the social structures, we have knowledge of individuals who fill certain (possibly overlapping) roles at the village, village cluster (regional), and district levels and have political or religious authority over the people. We consider these individuals to be Pashtun local leaders, and describe them each briefly here to provide an overview of who may have influence and at what levels. The roles and the corresponding spheres of influence are depicted in Figure 2-12. However, it is significant to note that researchers have observed diversity in the characteristics of these authorities, and more importantly each authority's relative power is very much context and locally dependent. In other words, Pashtun politics are highly person-centered [38]. As Rubin writes, "Power in villages or tribes does not reside in any one person or structure but in fluidly structured networks or influence. These networks are not based on any single principle: neither wealth nor kinship suffices to assure a man influence" (page 198) [34].

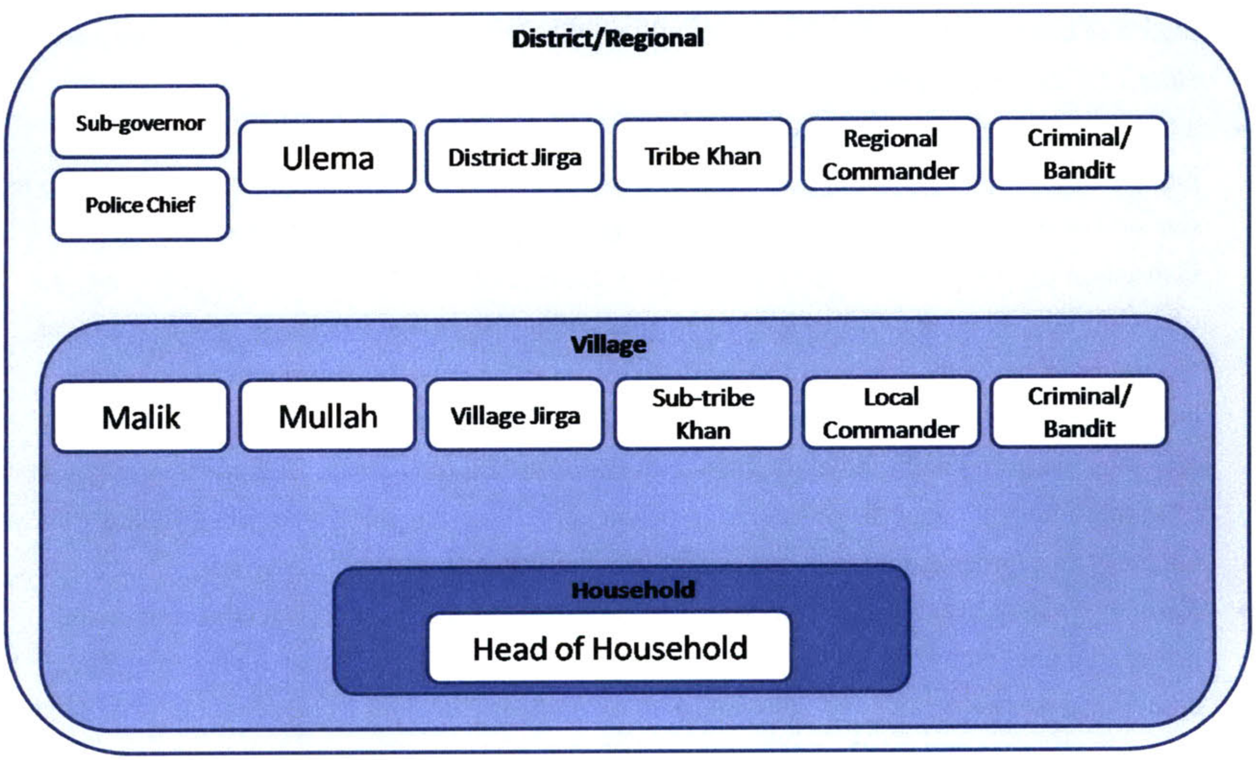

Figure 2-12: Pashtun Local Leaders and Spheres of Influence

- Head of Household. The oldest male or patriarch is often considered the head of the household [27] and holds undisputed authority within the household [29]. The household is the primary unit of locality among Afghans and may include several generations of the extended family [27].

- *Jirga* or council. A village *jirga* is a council made up the male elders of a village who have some level of respect within the community [39]. The *jirga* meets regularly, but not necessarily on a particular day, to discuss matters of importance to the whole village and to settle disputes. This body favors inaction because it requires consensus and cooperation among all members [39]. But when a decision is made, it is binding to all participants [30]. The decision may be enforced by the community militia, or *arbaki*, which is comprised of young unmarried men of the village [30]. There are multiple levels of *jirga*, from district/regional, provincial, and national. Higher (district/regional) level jirgas are comprised of the more influential or respected persons from lower level *jirgas* [40].
- *Malik* or village headman. An executive authority for the village. He is someone who is elected by the *jirga* to represent the village to the government. He communicates the community interests to the government and news and government policies back to the village. Because of his responsibilities, a *malik* is often required to be literate and may therefore come from a well-educated family within the village. A *malik* may also be a tribal elder or a landowner [39].
- *Mullah/Ulema* or Priest or Religious Scholar. A *mullah* is a religious leader and local judicial authority of the village; there may be several *mullahs* in a village, depending upon its size and population diversity [41]. They might or might not have had formal religious instruction of lower degrees from madrasas or local religious schools ([39], [42]). They are often literate. They are all financed by people within the village. Because of the particular role *mullahs* have in society, it may be difficult for other persons of influence (including landowners and *maliks*) to confront them publicly [39]. Those who are on the next level of religious hierarchy and scholarship above the *mullahs* are the *ulema*. The *ulema* are a higher religious authority and are considered to be keepers of the scriptural tradition of Islam. They hold higher degrees from madrasas and Islamic universities [42].
- *Khan* or tribal or sub-tribal leader. A sub-tribal *khan* is someone who is recognized as the leader of a *khel* (sub-tribe) within the village. He is usually someone with clear patrilineal descent, possesses wealth and land, and also exhibits a critical set of personal qualities [38]. These qualities include gallantry in war, superior rhetoric qualities, or sound judgment exhibited during *jirgas* [30]. But because of the underlying egalitarianism among Pashtuns, a *khan* may have a tenuous hold on his position, and be continuously compelled to convince the village of his leadership and authority [30]. In addition to the sub-tribe, there is a *khan* for the tribe as well.
- *Woluswal*, the district sub-governor. He is appointed by Afghanistan's President and reports to the provincial governors. He represents the government at the district-level and may assist in conflict resolution through his relationship with the district *jirga* or police [43]. While he

has a limited capacity of office, he is nevertheless influential through his own personal relationships and wields some power by acting as a 'gatekeeper' between the people and government services [43].

- *Ufiser polis*, District Police Chief. A representative of the government who leads the Afghan Police assigned in the district. In tandem with the district sub-governor, a police chief can wield authority and also positively or negatively affect attitudes towards ISAF and the Afghan government.
- *Mujahed* or *qumandan*, warlord or commander. A person who has amassed significant power through patronage (legal or illegal) and an armed private militia ([33], [38]). Warlords are often former mujahedeen and a product of the destabilization of society due to the Soviet-Afghan War and subsequent civil war. There are local and regional level commanders who exert various levels of influence [33].
- Criminal or mafia elements. A person involved in robbery, vandalism, kidnapping or the smuggling of arms or opium. Criminals can be influential at local/village level or have more expansive influence in the region [44].

Some recent polling results show that villagers report the presence of influential people at the local level, particularly traditional leaders (*maliks*, elders), *mullahs*, and their father (see Figure 2-13) ([45]). When asked who's opinion is more important to them, villagers reported their father, husband, and family most often (see Figure 2-14) ([45]). Also, rural Afghans rely upon local leaders for information significantly more than urban Afghans (see Figure 2-15) ([46]).

Overall, the effectiveness of these individual authorities are difficult to determine empirically, but case studies and field research indicate a strong loyalty or adherence to decisions made by these individuals or bodies ([33], [45], [30], [47]).[4]

[4] As examples, a *jirga*'s decision is binding to the whole village ([30]) and enforced with the mobilization of community militias ([30], [33]). Also, a *mullah*'s opinion on topics of religious concern are heavily weighted ([45], [47]).

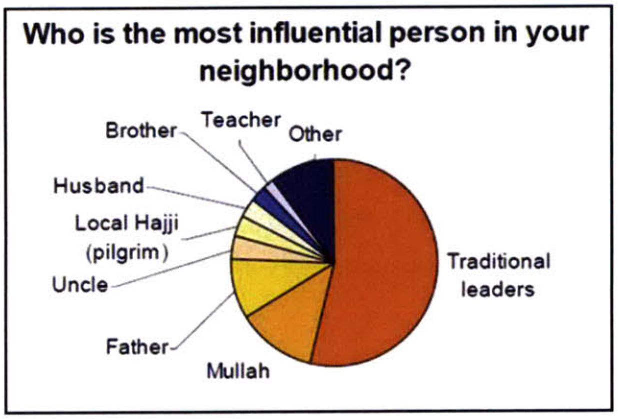

Figure 2-13: Survey Results of the Most Influential Person in the Neighborhood [45]

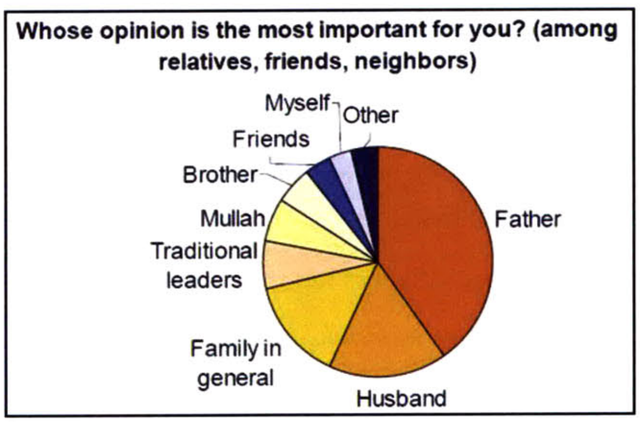

Figure 2-14: Survey Results of One's Own Opinion on who is Most Important [45]

	Radio, TV, national network Internet	Relative, local market, group or business or work associates	Mullah, community leaders	Community bulletin board, local newspaper	NGO/ Government	Political party
Categories	**Mass Media**	**Social Networks**	**Local Leader**	**Local Media**	**Official Staff**	**Political**
Kuchi	45	76	38	5	10	0
Rural	57	77	44	7	14	1
Urban	75	60	16	18	6	1
National	60	74	39	9	12	1

Figure 2-15: Reported Sources of Information by Percentage [46].

2.6.2 Taliban Insurgency Summary

In this section, we describe how the Taliban insurgency organizes, and the specific tactics they are known to employ in order to get the support of the population.

2.6.2.1 Composition

The Taliban as an enemy force in Afghanistan is generally comprised of three tiers of people with various levels of involvement in the insurgency.

- *Tier I: Full-time fighters*. These are the core militants who comprise a majority of the leadership and possess most of the training and technical expertise. They are estimated to comprise 25% of the total enemy force [48]. These individuals are also likely to be the more ideologically motivated to the Taliban movement [32].
- *Tier II: Local guerillas*. These individuals fight close to their home [48] and can be considered "part-time fighters" [32]. They are locally recruited by full-time fighters to provide operations support. They usually get involved for economic self-interest, as well as other reasons such as honor, prestige, or for local and tribal identity [48].
- *Tier III: Village underground*. This covert group of people provides an additional support structure for fighters. They help with reconnaissance, intelligence, and intimidation of government supporters [48].

The Taliban exhibit both a hierarchical structure for reporting and direction on policy matters, as well as a network structure for reporting and direction concerning operations. These two forms are captured in Figure 2-16.

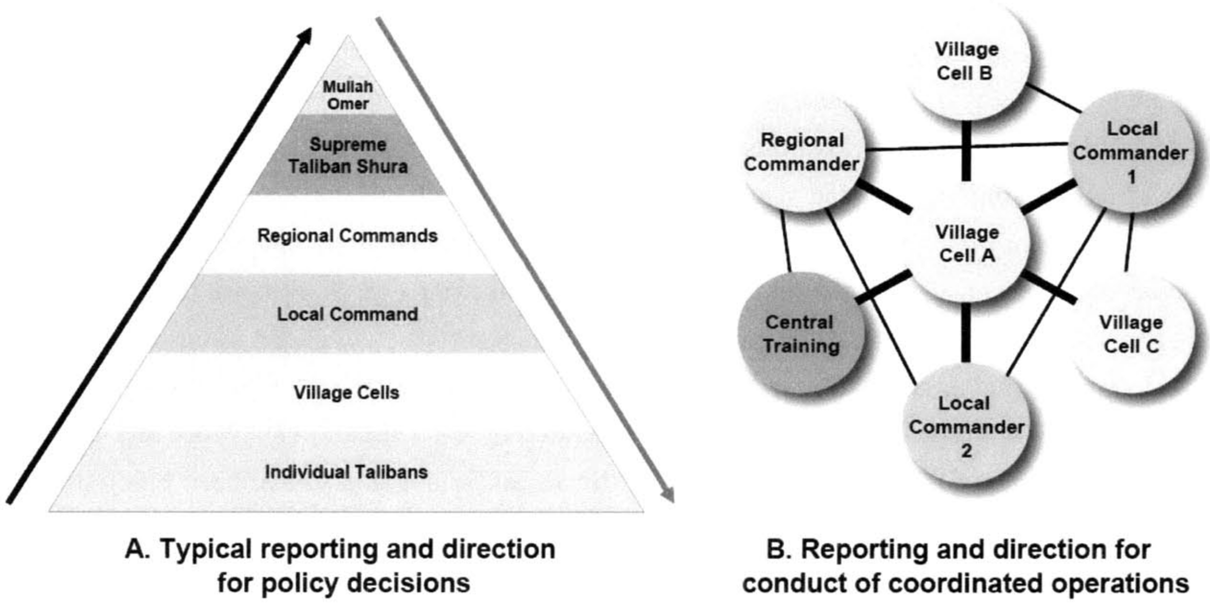

Figure 2-16: Taliban Organizational Structure [32]

2.6.2.2 Operations

We focus on the village cells of Taliban, which are usually comprised of 10-50 Tier II local guerillas or part-time fighters, and a small but undetermined number of Tier I full-time fighters [32]. The Taliban have known mechanisms of increasing infiltration into villages and communities.

- *Gain a foothold.* Village cells typically establish a presence in an area in one of two ways. First, a small armed group can originate from within tribal and territorial boundaries and declare itself "the local Taliban" [32]. They subsequently work to acquire recognition from the local or regional commander but also retain some latitude to conduct operations in cooperation with other village cells [32]. Another way the Taliban can originate is from outside tribal and territorial boundaries (possibly due to repulsion from the previous location of operations or an expansion of operations). In this method, the culturally-aware Taliban and local sympathizers would first approach the tribal elders for permission to enter tribal lands and villages. They would generally travel in small groups of 10-20 and identify those locations and groups of people who were hospitable to them [49].
- *Gradually increase control and strength.* Once the Taliban gained a foothold in the area, they systematically worked to marginalize the other power figures in the area. They would permit local leaders to speak openly of things agreeable to Taliban, but would silence any contrary opinions with threats and demonstrative acts of violence [49]. The Taliban are most effective at communicating at the local level via night letters[5] and interactions with the people ([50], [51]). Village cells are also responsible for its own recruitment, which "exploits family and clan loyalties, tribal lineage, personal friendships, social networks, *madrassa* alumni circles, and shared interests" [32].
- *Inflict a campaign of violence and intimidation.* If the Taliban experienced any resistance to control or influence, they would conduct a methodical campaign of violence to remove the opposition known as "armed propaganda" [48]. Such activities included intimidation, kidnappings and assassinations ([52], [32]). For example, from 2005-2006 twenty pro-government *mullahs* were killed and forty wounded by the Taliban [49]. More recently in 2009, more than fifty Afghan government officials and tribal elders have been killed by the Taliban [52]. For every one killed, there are numerous others who are forced to flee the area as refugees, which in turn further weaken the resistance to the Taliban.

[5] Night letters, known as *shabnamah*, are written warnings and threats often posted on the doors of mosques or homes of known government supporters. The Taliban messages in them resonate with the populace because they are powerful and easy-to-understand. The messages include how both the Afghan Government and the Coalition are responsible for "collateral damage and threats to poppy harvest and tribal customs" [50].

2.6.3 US Army COIN in Afghanistan

Recently, General Stanley McChrystal, the new commander of the International Security Assistance Force (ISAF) in Afghanistan[6], signaled a shift in COIN strategy in Afghanistan from killing or capturing insurgents towards 1) protecting the population, 2) providing improved governance, 3) winning the war of perceptions, and 4) embracing the people [15]. Critically, he also instructed his soldiers to

> Build connections... Afghan culture is founded on personal relationships. Earning the trust of the people is a large part of our mission. Build relationships with tribal, community, and religious leaders. Success requires communication, collaboration, and cooperation [15].

In this section, we discuss the increased emphasis on finding and influencing key local leaders as a major tenet of US COIN doctrine in Afghanistan.

2.6.3.1 Lessons from Iraq on Finding Key Local Leaders

Counterinsurgency strategy, as explained in Section 2.4, is fundamentally about winning the support of the population through a combination of efforts that includes demonstrating the government's legitimacy as well as unequivocally protecting the people from the insurgents. However, in a resource-constrained environment (i.e., limited troops and time), a major difficulty is determining a strategy of actions that wins even more of the population by considering societal factors and local power structures.

In recent history, one can look at the results of the US strategy in Anbar Province, Iraq from 2006-2007 to see the rapidly cascading effects of winning over and supporting key leaders. While not always effective [21], the US military conducted a deliberate information engagement campaign with tribal leaders and eventually recognized and actively supported efforts by *sheikhs* to resist Al Qaeda [53]. The effect on decreasing violence was dramatic when these *sheikhs*, who commanded their large tribes and militias, allied together to side with the US and against Al Qaeda [53], [21].

Afghanistan is likewise embroiled in an insurgency, but social dynamics are much different there than in Iraq. There is general consensus that a large tribal mobilization solution does not exist

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[6] General McChrystal was selected by the President of the United States and confirmed by the US Senate in June 2009 to assume command of the NATO Coalition in Afghanistan.

for Afghanistan ([54], [31], [48], [55], [30]). While Arab tribes tend to be more hierarchical, Pashtun tribes are much more decentralized [48]. Indeed, very tenuous alliances form among Afghans which can change quickly for a multitude of reasons [54]. A recent white paper from the US Army Afghanistan Research Reachback Center states,

> [T]he way people in rural Afghanistan organize themselves is so different from rural Iraqi culture that calling them both 'tribes' is deceptive. 'Tribes' in Afghanistan do not act as unified groups, as they have recently in Iraq. For the most part they are not hierarchical, meaning there is no 'chief' with whom to negotiate (and from whom to expect results) [31].

Nevertheless, researchers and military strategists alike seem to conclude that finding the key influential people within Afghan society (if not at the tribal-level, then at another reasonable level) is an important step in winning ([10], [54], [31], [56], [57]) They prescribe that pro-government forces should identify local community leaders who have respect among the population, earn their support, and use their influence to "wean" most of tier II and III away from the insurgency [48].

However, finding these key leaders is not enough to guarantee success. Protecting them is paramount, especially after a person has decided to support the government at high risk [54]. Kilcullen writes,

> It is extremely important, in analyzing an insurgency, to be able to put oneself in the shoes of local community leaders. In insurgencies and other forms of civil war, community leaders and tribal elders find themselves in a situation of terrifying uncertainty, with multiple armed actors– insurgents, militias, warlords, the police and military, terrorist cells– competing for their loyalty and threatening them with violence unless they comply… counterinsurgency measures must be designed to help the population to choose between the government and the insurgent, and to enforce that choice once made. This implies the paramount moral obligation to protect and defend populations that have made the dangerous choice to side with the government [48].

Furthermore, winning over the right number of local leaders is an important consideration. Constrained by resources, a counterinsurgent ideally wants to win over and protect a critical mass of key leaders that in turn achieves cascading effects on the population and other key leaders [54].

2.6.3.2 Reconciliation with the Taliban

The problem of identifying the key leaders to engage with has a close corollary: how to co-opt them so that their now favorable influences can propagate to others. In a conflict environment such as COIN, one might identify key leaders who are truly neutral as well as those who have leanings towards the insurgency or even actively supported them in the past. This situation naturally leads to questions about reconciliation with or "flipping" the Taliban [54]. In fact, within the past year, US and Afghan politicians, US military officials, and researchers have increasingly discussed if and how to reconcile with the some portions of the Taliban insurgency ([54], [58]). A few researchers have suggested that dramatic allegiance flipping is indeed plausible ([31], [54], [58]), and may be based on the motivations of the lower-level fighters including the desire to be on the winning side [54], desire for employment or money [58], or just simply pressure "by internal dissension or external forces" [31]. However, all seem to agree that the actual implementation of a coherent policy would be extremely difficult and complex.

2.6.4 Difficulties in Nonlethal Targeting in Afghanistan

> In Afghanistan, things are rarely as they seem, and the outcomes of actions we take, however well-intended, are often different from what we expect. If you pull the lever, the outcome is not what you have been programmed to think. For example, digging a well sounds quite simple. How could you do anything wrong by digging a well to give people clean water? Where you build that well, who controls that water, and what water it taps into all have tremendous implications and create great passion. If you build a well in the wrong place in a village, you may have shifted the basis of power in that village. If you tap into underground water, you give power to the owner of that well that they did not have before, because the traditional irrigation system was community-owned. If you dig a well and contract it to one person or group over another, you make a decision that, perhaps in your ignorance, tips the balance of power, or perception thereof, in that village. Therefore, with a completely altruistic aim of building a well, you can create divisiveness or give the impression that you, from the outside, do not understand what is going on or that you have sided with one element or another, yet all you tried to do is provide water [59].

These remarks by General McChrystal highlight some of the unique challenges with non-lethal targeting in Afghanistan. As stated from the outset, the operational environment in COIN is extremely complex. Because the goal is to ultimately gain support of the population, units must thoroughly understand and leverage a whole host of variables, both operational and mission (PMESII-PT and METT-TC), in order to win. Given the strength of the Taliban insurgency and

the unique cultural and tribal conditions in Afghanistan, the problem of nonlethal targeting is even more complex. Here we discuss the difficulties of nonlethal targeting in the *Decide* and *Assess* functions.

2.6.4.1 Difficulties in the Decide Function

The decision function's output can be divided into several broad subtasks: who to target, in what priority, and with what means. Who to target is addressed in the development of the HVTL and has several challenges including 1) determining a person's value, 2) measuring the strength of a person's influence, 3) determining the extent of a person's influence on others, 4) measuring a person's intentions or motivations, 5) determining whether a person is able to be co-opted . Target priority is addressed in the development of the HPTL and has additional challenges including: 1) the uncertainty of determining a person's value, and 2) the uncertain opportunity costs of targeting another person. Deciding with what means to influence is addressed in development of the friendly COAs. It adds to the list of challenges including, 1) determining who is the best 'ambassador' (i.e. unit leader) to that person, 2) what nonlethal activity or activities can achieve the desired effects, and 3) how much the unit must be prepared to expend to influence the person.

2.6.4.2 Difficulties in the Assess Function

The *Assess* function requires the unit be able to judge the effectiveness of the targeting effort as well as determine the opportunities for reengaging the person. Judging effectiveness is a difficult task because that staff may not be able to 1) measure the true impact on the targeted person 2) determine how long-term the impact is, and 3) determine the second- and third-order effects on other connected persons. The additional difficulties for finding the opportunities for reengagement also include 1) determining how many times or for how long the targeting effort should be made, and 2) determining what other persons are now more vulnerable to favorable influence.

The difficulties with nonlethal targeting in Afghanistan are indeed immense. This work intends to address some of those difficulties by presenting an integrated decision support tool that helps military professionals better perform the *Decide* function. The models and tool are discussed in the following chapter.

3 Modeling Approach and Formulation

3.1 Modeling approach

In Chapter 2 we presented counterinsurgency as a politico-military struggle for the support of the population, detailed some of the current research on Pashtun Afghan social structure, and explored some implications of influencing local leaders to more effectively win that popular support. Furthermore, we explained how the US Army currently conducts nonlethal targeting and identified difficulties and uncertainties in the *Decide* function of selecting individuals to influence. To enhance the analysis required for nonlethal targeting among Pashtuns, we propose the inclusion of social influence modeling into the process.

This social influence modeling we put forward is actually comprised of three different models; the first is the *Afghan COIN social influence model* (a tractable agent model to represent how attitudes of local leaders are affected by repeated interactions with other local leaders, insurgents, and counterinsurgents), the second is the *network generation model* (to arrive at a reasonable representation of a Pashtun district-level, opinion leader social network), and the third is the *nonlethal targeting model*. The functional overview of these models is shown in Figure 3-1. Predicated on our social influence model, we developed the nonlethal targeting model as a nonlinear programming (NLP) optimization formulation that identifies the k-agents to target nonlethally in order to have the greatest expected effect on increasing favorable attitudes among the population. It is important to note that we formulated this nonlethal targeting problem as a modified assignment problem on the generated social network. The goal was to "assign" a fixed number of US Agents to k local leaders in an opinion leader social network in order to optimally influence the expected long-term attitude of the population in favor of the US forces. In a similar vein to other classical assignment problems[7], we do not prescribe *how* to influence (i.e., how to accomplish the assignment), but we do provide insight into the best use of resources that achieve the desired favorable influence (as will be shown by experiments in Chapter 4).

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[7] For example, the static weapon-target assignment problem (WTA) tries to minimize the total expected survivability of n targets by assigning a selected number of m different type weapons ([107], [108]).

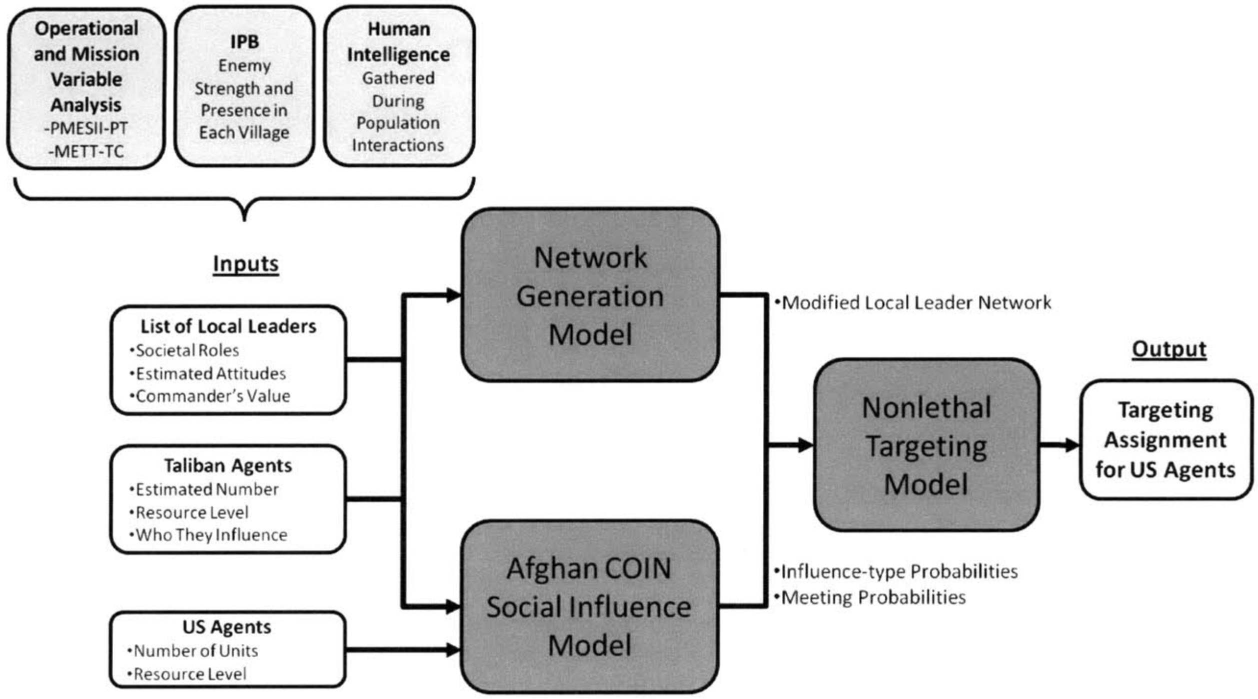

Figure 3-1: Functional Overview of the Models

3.2 Related Literature

In this section, we highlight several strands of related literature to this work in order to convey the richness of the field and the scholarship devoted to these ideas.

3.2.1 Social Science Literature on Opinion Leaders and Influential People

Opinion leadership has been an area of much interest in social science since Katz and Lazarsfeld [60] first hypothesized that a small number of individuals play an important role in shaping public opinion. They developed the "two-step" model of communication to explain the diffusion of innovations, ideas, and even commercial products: first from the media to the opinion leaders, and then from the opinion leaders to their primary groups (social circles that "actively influence and support most of an individual's opinion, attitudes, and actions" ([60], pg. 48). Interestingly, Katz and Lazarsfeld said that these individuals were not necessarily the public or hierarchical leaders, but rather were ones much less well known but who still had tremendous influence on the people they know (like neighbors, relatives, coworkers, and friends) [60]. Numerous researchers have since criticized the original formulation of opinion leadership and subsequently proposed modifications on how to identify them in societies (detailed in Weimann [61]). One such modification was the Personality Strength (PS) Scale methodology, which confirmed a

previously critical observation [62] that "influentials"[8] actually tended to be on higher social strata [63]. In addition, research suggests that the variable for being an "influential" is in fact continuous rather than a simple dichotomy, and that influence is transmitted via a multi-step flow (horizontal/vertical, direct/indirect, and downward/upward) rather than a simple two-step flow [61]. Still others take exception to the identification of influential people altogether. Emerson stated that contrary to the belief that a particular person is "influential" or "powerful", in fact the idea of power or influence is a "property of the social relation, not an attribute of the actor" [64] .

An additional complication to identifying influential individuals or isolating the influence process is the fact that individuals also determine who they interact with. As Lazer [65] observed, individuals are not only passively affected by their neighbors, but also often actively chose who those neighbors are. In order to understand the origin of a person's beliefs or attitudes, one must examine both processes [65].

3.2.2 Opinion Dynamics Literature

Beyond descriptive social sciences, researchers in other fields have tried to develop mathematical models to explain how an individual's beliefs and attitudes can change due to its interactions with others. Early on, Abelson formulated an elemental model that characterized how a pair-wise interaction of people can affect their scalar-value attitudes [66]. This effect was a function of the "persuasiveness" of each individual and the difference in their attitudes, and the effect on all individuals can be written as a system of differential equations. Furthermore, he identified the dilemma that while such mathematical models lead to a universal agreement among all agents[9], there are certainly cases in which this does not occur in real life. He concluded by mentioning some possible variants to the model which would not necessarily lead to a consensus. Later, DeGroot used the theory of Markov chains to model the weight an individual gives to the opinion of a deterministic set of neighbors and subsequently calculated the consensus opinion as the sum product of the steady-state 'probabilities' (opinion weights) and the initial opinions [67]. While he explained that a consensus occurs only when the states of the Markov chain are recurrent and aperiodic, he failed to mention how the model should be

[8] The term "influentials" was used to distinguish the revised conceptualization of opinion leaders from the original conceptualization by Katz and Lazarsfeld.

[9] We use the phrase "universal agreement among all agents" as the definition of consensus.

amended to account for the diversity of opinions in real life ([68], [69]). Subsequently, Friedkin and Johnsen developed the structural theory of social influence, which uses the model of a system of linear equations to explicitly consider how non-consensus opinion distributions can occur. In this model, an individual's future opinion is a convex combination of the person's exogenous initial opinion and the endogenous weighted current opinion of his neighbors ([69], [70]). This was shortly followed by work from Deffuant, et al [71] and Hegselmann and Krause [72] who each developed the bounded confidence model of continuous opinion dynamics that specified a threshold for agent interaction (i.e., interactions and influence could only take place if the opinions of two agents were within some bound of each other). Later Deffuant further studied the effect of extremist agents on a variant of the bounded confidence model [73]. In his work, an agent has both an opinion and an uncertainty that is expressed as a confidence interval around its opinion. Extremist agents have not only extreme opinions, but also less uncertainty (or more influence). His research explored the parameter space in which extremist agents caused the polarization of the rest of the agents' opinions in a complete graph.

Lastly, the models most incident to this work are the spread of misinformation model developed by Acemoglu, Ozdaglar, and ParandehGheibi [6] and the persistent disagreement model developed by Acemoglu, Como, Fagnani, and Ozdaglar [7]. The spread of misinformation model characterized agent beliefs in a social network in the midst of influential agents. This model posited that the pair-wise interactions between agents in a network were probabilistic in two ways: 1) in the frequency of their meeting, and 2) in the type of interaction (averaging, forceful, or identity) between the agents. Operating on the assumption that everybody in the network is influenced by someone else ("no man is an island"), this work proved that the presence of forceful agents (agents who had a positive probability of forcefully influencing another agent) leads to the formation of a consensus among all agents, but that consensus is a random variable with some unknown distribution [6]. The researchers also found a bound for the difference between the consensus in the midst of forceful agents and the consensus without them. The persistent disagreement model extends the misinformation model further by designating non-homogenous stubborn agents (those whose disparate opinions do not change) and trying to characterize the resulting expected long-term attitudes in the network that necessarily do not reach a consensus [7].

3.2.3 Key Person Problem (KPP) Literature

Another growing field of research is the identification of key people in groups of individuals who can facilitate the diffusion of an idea or behavior. This strand of literature tries to solve the Key Person Problem (KPP), a phrase first used by Borgatti [74]. Borgatti developed two new measures of centrality of an agent in a network. The first one quantified the disconnectedness resulting from the removal of k-agents from a network. The second one quantified the connectedness of k-agents to the rest of the agents in a network. Using the new formulations of centrality, he then could find the k-agents that maximally disconnected or maximally connected the network with a simple greedy algorithm [74]. In a related problem, Kempe, Kleinburg, and Tardos developed an optimization formulation for finding the k-agents whose directed activation would lead to the maximum number of agent activations in the entire network. They used both the threshold and independent cascade models of diffusion in their work [75]. While this was an NP-hard problem, the researchers showed that a hill-climbing algorithm would guarantee a 63%-approximate solution [75]. Overall, the KPP literature we found, while related to this work in sharing the goal of selecting the best k-agents for some objective, falls short by modeling the diffusion of binary behaviors, rather than trying to affect continuous attitudes.

3.2.4 Afghan Application of Network Modeling

In research more applicable to Afghanistan, Geller developed an agent-based computational model for analyzing the formation of *qawms* (traditional solidarity groups) among Afghan agents [36] as well as tested the diffusion of information on the resulting network [76]. Geller first identified 10 actor-types common in Afghan society and differentiated the actor-types into two categories: "strongmen" and "ordinary agents" [36]. A representative sample of assorted agents then drew upon a model of endorsements in exchange for goods and services and formed interconnected *qawms*. With the network in place, Geller also tested the diffusion of messages on it and found that propagating messages from "strongmen" led to a faster diffusion in the network than seeding from a regular agent [76].

3.3 Afghan COIN Social Influence Model

Having shown the amount of scholarly and diverse literature on which this work is based, we now proceed to describe the first of the three models. The Afghan COIN social influence model

is a tractable agent model[10] that allows us to analyze the effects of repeated interactions among local leaders, Taliban insurgents, and US counterinsurgents on the attitudes of Afghan population. It is a modification of the spread of misinformation model from Acemoglu, et al. [6], and was enhanced to suit the context of a counterinsurgency in Afghanistan.

3.3.1 Scope of the Model

Before we discuss model specifics, it is important to explain its scope. In this work we are prescribing a process to analyze the influence of local leaders, insurgents, and counterinsurgents on attitude dynamics of a fixed population given some coarse but realistically attainable data measurements. We note upfront that in reality there is tremendous variability in local politics between different villages and districts ([38], [34]). Given this variability, it is difficult to determine an appropriate level of analysis when considering the effects of leaders on population sentiments that fits *all* of Afghanistan. There are certainly leaders at every level of analysis, but whether those leaders have any effective influence on the population to support one side or the other in a counterinsurgency is much more uncertain. The model we prescribe must be *carefully* parameterized to match the local analysis of the operational and mission variables discussed in Section 2.2.1. Depending upon the particular area, different local leaders at different levels may effectively exert influence on the population.

We cautiously proceed by proposing a scope that may be applicable for this social influence analysis. As a method of practice for better command and control, US Army units divide up its area of operations (AO) into smaller sectors to be supervised by subordinate commands. More recently in portions of eastern Afghanistan, a battalion typically takes responsibility for a province, while a subordinate company takes responsibility for one or two districts within that province ([77], [78]). It is this latter level, specifically a company unit operating in a rural Pashtun district, which we suggest as an appropriate starting point for our social influence modeling approach. We base this suggestion upon the fact that the company is the smallest conventional unit that interacts closely with the population and has resources for an intelligence analytic capability, as well as anthropological findings that 1) rural Afghan populations tend to be have tighter knit communities (*qawms*) [37], and 2) rural populations tend to be more reliant

[10] Tractable agent modeling is a modeling technique that analytically derives the emergent collective behavior from the individual decisions of a group of autonomous entities called agents.

on traditional authorities [31]. We continue by discussing the basic building blocks of the COIN social influence model.

3.3.2 Agent Properties

3.3.2.1 Agent identification

With an understanding of COIN as a struggle for the support of the population, we model two types of actors generically found in the counterinsurgency environment. We will use the term *agent* to signify these actors and eventually represent them as *nodes* in network. The first type is the ideologically motivated agent consisting of Taliban insurgents and US counterinsurgents, all of whose attitudes for their causes are immutable. We use S to denote this set of "stubborn" agents, where US and TB represent the set of US and Taliban agents, respectively, and $S = US \cup TB$. The second type of agent is the Pashtun local leader who has a mutable attitude on supporting either side of the counterinsurgency. We use $\mathcal{A}$ to denote this set of all others. It is important to note that we do not model every agent as necessarily representing only one person. In general, we consider each agent to be representative of a number of people who collectively exhibit the same attitude, or who expend resources on others (time, attention) at the same rate. According to this concept of an agent or node, we made the following modeling decisions:

- *Head of household.* We represent all individual household members by a single male head of household node. Based on the primacy of the head of households within the family ([45], [29]), we assume that attitudes are homogeneous within the same household, or are too suppressed to matter.
- *All other villagers and officials.* We represent each of the local leaders within the village and district to be its own distinct node. In our analysis of typical Pashtun villages and districts, we identified those most likely to be considered a local leader (as listed and described in Section 2.6.1.2). However, once again, we acknowledge tremendous variability across villages and districts. Not all villages will have individuals who fill every single role identified. Also, there are other roles beyond those listed, such as businessmen and other government officials, who may have influence on the local population. Further still, individuals may fill several roles, thus overlapping in their spheres of influence. It is critical counterinsurgents conduct a thorough analysis of the population to identify all those who need to be represented in the model.

- *Taliban insurgents.* We initially represent a village cell of insurgents as a single node under the village cell leader since all operations by the cell are likely to be conducted in concert. However, we also allow for the possibility of relaxing this assumption when we consider that each insurgent within the cell could also intimidate and suppress the population at different rates.
- *US counterinsurgents.* We represent US counterinsurgents as 3 different entities: the platoon leader, the company commander, and the battalion commander. While all their subordinate soldiers support missions in COIN, generally only these three types of leaders may conduct nonlethal activities at the district level in the form of meetings and other activities listed in Section 2.5.1. Each of these entities can simultaneously conduct separate engagements, all at different rates.

We make a limiting assumption that the time horizon of analysis is such that all agents are considered fixed in the environment; that is, no new agents appear or and no existing agents disappear. We denote the set of all agents as $V = S \cup \mathcal{A}$, and $|V| = n$.

3.3.2.2 Occurrence of Interactions

We assume that each agent meets another agent in a pair-wise interaction as a Poisson process with rate 1, independent of all other agents [6]. Therefore, in a network of n agents, we say that interactions over all agents occur as a Poisson process with rate n. In assuming a Poisson process of interactions, we are claiming that there is at most one interaction at any given time. Furthermore, we index these interactions over all the agents with $k, k \geq 1$. Lastly, note that the time between interactions is clearly not fixed.

3.3.2.3 Attitude Estimation

An agent's attitude towards counterinsurgents can be measured in several ways, e.g., polling instruments [46], conducting face-to-face meetings and focus groups [57], and subjective assessments of population's behaviors and demeanor during interactions. This work does not prescribe a method of detection of individual attitudes, but assumes that they can be measured reasonably, accurately, and be distilled into a single numeric value.

We model an agent's attitude towards the counterinsurgents as a continuous random variable that takes on a scalar value at each interaction occurrence (over all the agents). We denote $X_i(k)$ as agent i's attitude at the k-th interaction, where $X_i(k) \in [-0.5,0.5]$. A negative (or positive)

value means low (or high) favorability towards the counterinsurgents, and zero means neutral. This spectrum of attitudes is depicted in Figure 3-2. Extreme points along the scale denote a greater strength of attitude [73]. In our model, the ideologically motivated agents, the US counterinsurgents and the Taliban insurgents, possess immutable attitudes which remain at the extreme points and do not change over time, i.e., $X_i(k) = -0.5,\ \forall\, i \in TB, \forall\, k \geq 0$ and $X_i(k) = +0.5,\ \forall\, i \in US, \forall\, k \geq 0$.

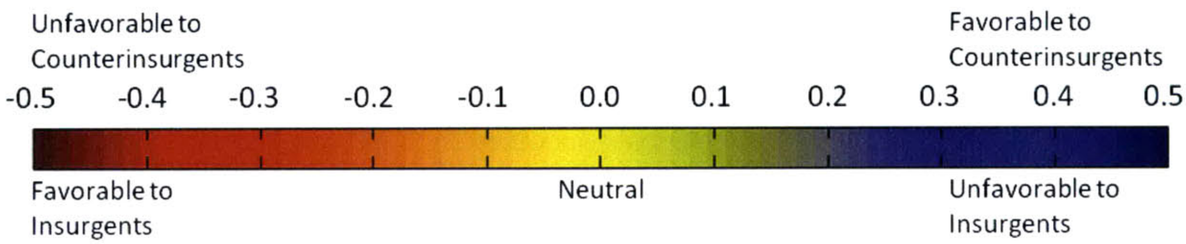

Figure 3-2: Attitude Scale

3.3.3 Attitude Dynamics

We model the attitude dynamics of all agents as a Markov chain, where the state of the system is the set of agent attitudes at a particular interaction k, i.e., $X_i(k)\ \forall\, i \in V$, and state transitions are determined probabilistically from the pair-wise interactions between agents connected in a network. The state of the system is also denoted as $\boldsymbol{X}(k) \in \mathbb{R}^{n\times 1}$, which is the vector of random variables for the attitude of all agents in set V at the k-th interaction. The Markov property [79] we assume is that the state of all agent attitudes will have the same transition probabilities to another state of attitudes given the current state, regardless of the state history or how that state was reached. Specifically, mutable agents change their attitudes as a result of memory-less, person-to-person interactions with neighbors in the network[11]. In this work, we broadly define interactions as any exchange of information or ideas, including discussion, appeals, arguments, threats, or intimidation.

Furthermore, we assume that every agent, when interacting with another agent, might retain some fraction, called self-weight, of its own attitude. Any single agent may retain different amounts of their attitude depending on who they interact with. We denote this with $\varepsilon_{ij} \in [0,1]$,

[11] This assumption of agents' memory-less adjustments of attitudes is based on some research about how Afghans are notorious for changing alliances in armed conflicts to be on the winning side [54] or even for economic incentives [58].

which is the fraction of agent i's attitude that it retains upon interaction with agent j. The order of the subscripts is significant: the first subscript signifies the agent's self-weight when interacting with the agent signified by the second subscript. Note that the order of the subscripts does not signify the order of the interaction, i.e., agent i's self-weight when interacting with agent j is the same regardless of the order of the interaction. We also assume an agent's self-weight when interacting with another particular agent is fixed, and that time does not affect how much each agent retains of its attitude. Additionally, we view this self-weight as an endogenous value to the individual and distinct from the persuasiveness of the other agent in the interaction.

The dynamics of the model at each interaction k, modified slightly from Acemoglu, et al. [6], proceed as follows:

- Agent i initiates an interaction by some probability distribution over the population. This distribution could be uniform (meaning every agent has an equal chance to initiate) or some skewed distribution (meaning some agents may instigate interactions more frequently). From among its neighbors, agent i then selects agent j uniformly at random with probability p_{ij}.
- Conditioned on agents i and j meeting, one of three types of pair-wise interactions occur [6]:

I. *Averaging.* With probability β_{ij}, they reach a consensus equal to the average of their prior attitudes:

$$X_i(k+1) = X_j(k+1) = \frac{X_i(k) + X_j(k)}{2} \tag{3.1}$$

II. *Forceful.* With probability α_{ij}, agent j 'forcefully' imparts $(1-\varepsilon_{ij})$ of its attitude on agent i:

$$\begin{cases} X_i(k+1) = \varepsilon_{ij} \cdot X_i(k) + (1-\varepsilon_{ij}) \cdot X_j(k) \\ X_j(k+1) = X_j(k) \end{cases} \tag{3.2}$$

III. *Identity.* With probability γ_{ij}, both agents exhibit no change in attitude:

$$\begin{cases} X_i(k+1) = X_i(k) \\ X_j(k+1) = X_j(k) \end{cases} \tag{3.3}$$

and $\beta_{ij} + \alpha_{ij} + \gamma_{ij} = 1$.

There are broad interpretations for each of these types of interactions. Interaction (3.1), called the averaging interaction, effectively represents both agents communicating and discussing their

own attitudes about supporting or not supporting the counterinsurgency, and parting with some agreement on a middle ground. Interaction (3.2), called the forceful interaction, can be interpreted as agent *i* essentially adopting agent *j*'s attitude because agent *j* acts as its opinion leader, or agent *j* uses some form of effective persuasion or influence. Note that only agent *i*'s attitude changes in this interaction. Interaction (3.3), called the identity interaction, occurs when agents with disparate beliefs interact but fail to concede, and subsequently retain the same attitudes as before. As a whole, these interaction types provide a richer set of dynamics than models which support only binary decisions [73].

We further note that the interaction dynamics allow for essentially two effects: moving *towards* someone else's attitude, or remaining the same. In this simplified model, we have not formulated a dynamic where an agent moves *away* from someone else's attitude. Abelson termed this as the "boomerang effect" and reasoned that it occurs when two partisan individuals knowingly choose positions that are intended to oppose the other ([66]: 153). This extension to the model is potentially applicable to Pashtuns, who are known to have inter- and intra-*qawm* conflicts [31]. However, such a model modification is left for future work.

3.3.3.1 Influence estimation

In our model, the influence that agent *j* exerts over agent *i* is probabilistic and governed by the specific parameters: β_{ij}, α_{ij}, γ_{ij} (which we call the interaction-type probabilities), and ε_{ij} (the self-weight). We acknowledge that collecting such 'soft' data (like the strength of a person's influence over another or the self-assurance of a person) is hard in a controlled environment and *extremely* difficult among populations in conflict environments such as insurgencies. Nevertheless, we proceed by reasoning through the influence estimation of each of the two different types of agents: the mutable local leaders, and the immutable insurgents and counterinsurgents.

For the mutable local leaders, we draw upon our knowledge of rural Pashtun society and choose to differentiate opinion leaders by the largest sphere in which they exert influence: at the household, village, and regional/district levels. Those who exert influence only within their own household, we characterize their level of forcefulness as *regular*. Those who exert influence further to within the village (a village leader), we characterize as $forceful_0$. And finally, those who exert influence further still to within the region (a district/regional leader), we characterize

as *forceful₁*. Let R be the set of *regular* agents, F_0 be the set of *forceful₀* agents, and F_1 be the set of *forceful₁* agents. For each pair of agents, each with a level of forcefulness, we determine a reasonable assignment rule of interaction-type probabilities. For example, we may initially choose the following three sets of parameterization rules:

$$\begin{cases} \beta_{ij}=1.0, \ \alpha_{ij}=0.0, \ \gamma_{ij}=0.0, & \text{if } i,j \in R \\ \beta_{ij}=0.0, \ \alpha_{ij}=1.0, \ \gamma_{ij}=0.0, & \text{if } i \in R, j \in F_0 \cup F_1 \end{cases}$$

The interpretation of this first set is that a villager who is simply a head of household ($\in R$) always reaches a pair-wise consensus with another head of household, and always adopts a village leader's attitude.

$$\begin{cases} \beta_{ij}=0.1, \ \alpha_{ij}=0.0, \ \gamma_{ij}=0.9, & \text{if } i,j \in F_0 \\ \beta_{ij}=0.1, \ \alpha_{ij}=0.0, \ \gamma_{ij}=0.9, & \text{if } i,j \in F_1 \end{cases}$$

The interpretation of this second is that a village leader ($\in F_0$) or district/regional leader ($\in F_1$) reaches a pair-wise consensus with another leader of the same level with small probability, but would otherwise retain his attitude.

$$\{\beta_{ij}=0.1, \ \alpha_{ij}=0.4, \ \gamma_{ij}=0.5, \quad \text{if } i \in F_0, j \in F_1$$

The interpretation of this last set is that a village leader reaches a pair-wise consensus with a district/regional leader with small probability, and either adopts the district/regional leader's attitude or retains his own attitude with greater probability.

This is admittedly a coarse means of determining the interaction-type probability matrices (β, α, γ), but is informed by studies of Pashtun society. In essence, the difference in levels of forcefulness as determined by societal position between agents (data more easily obtained by soldiers working with the population) is used as an estimate for the relative influence between the agents. As soldiers understand more of the interpersonal relationships between pairs of people, it would be possible to assign more accurate estimates of the probabilities. For example, if soldiers in a particular area detect that the villagers seem more cohesive with each other but more suspicious of district-level leaders, one may capture this by increasing the forceful interaction-type probability between village leaders and heads of household, and decreasing the forceful interaction-type probability between district leaders and village leaders. One would simply to adjust the interaction-probabilities appropriately to reflect the perceived sentiments on the ground.

We now consider how to characterize the influence of the immutable agents, the US counterinsurgents and Taliban insurgents. We add two types of *forceful₂* agents to represent the US counterinsurgent and Taliban insurgent (where $X_{US}(k) = 0.5$ and $X_{TB}(k) = -0.5$ for all k). Let F_2 be the set of these '*forceful₂*' agents. In the same manner of assigning the other interaction-type probabilities, we can reasonably do the same for the *forceful₂* agents:

$$\begin{cases} \beta_{ij}=0.0,\ \alpha_{ij}=1.0,\ \gamma_{ij}=0.0, & \text{if } i \in R \cup F_0 \cup F_1, j \in F_2 \\ \beta_{ij}=0.0,\ \alpha_{ij}=0.0,\ \gamma_{ij}=1.0, & \text{if } i,j \in F_2 \end{cases}$$

The interpretation here is that the US and Taliban agents can always persuade another local leader to adopt its extreme attitude. While this is an example of a possible parameterization, throughout this work we say that it fits for Taliban agents because their use of armed propaganda and violence is very effective at persuading the population. However, we will later explore the case when US agents do not have this certainty of persuasion, a more realistic case due to uncertainty of the effectiveness of the nonlethal actions available to them.

3.3.4 Analytic Formulation of Expected Long-Term Attitudes

While the pair-wise interactions between two agents in the social influence model are fairly simple, the entire system itself becomes quite complex for many agents connected in large networks. However, our modeling technique is conducive to simulation and allows us to study the emergent behavior of the entire system. Such simulations have been used extensively in researching emergent behavior or the propagation of beliefs or actions in social networks ([80], [4]). We discuss our simulation in the following chapter. Moreover, by employing tractable agent modeling, we were also able to compute the *expected long-term* attitudes for each agent analytically. In this section, we explain the derivation for this result and discuss its implications for our optimization formulation.

3.3.4.1 Derivation

We recall that there were three interaction-types, averaging, forceful, and identity, which occurred with probabilities β_{ij}, α_{ij}, γ_{ij}, respectively. We begin by writing the conditional expected value of the resulting attitudes for a single pair-wise interaction between agents i and j:

$$\mathbf{E}[X_i(k+1)|\boldsymbol{X}(k)] = \beta_{ij}\left(\frac{X_i(k)}{2} + \frac{X_j(k)}{2}\right) + \alpha_{ij}\left[\varepsilon_{ij} \cdot X_i(k) + \left(1-\varepsilon_{ij}\right) \cdot X_j(k)\right] + \gamma_{ij} \cdot X_i(k)$$

Factoring all the terms, grouping like terms of $X_i(k)$ and $X_j(k)$, and substituting in $\gamma_{ij} = 1 - \beta_{ij} + \alpha_{ij}$ gives us:

$$\begin{aligned}\mathbf{E}[X_i(k+1)|\boldsymbol{X}(k)] &= \beta_{ij}\frac{X_i(k)}{2} + \alpha_{ij}\cdot\varepsilon_{ij}\cdot X_i(k) + \gamma_{ij}\cdot X_i(k) + \beta_{ij}\frac{X_j(k)}{2} + \alpha_{ij}\left(1-\varepsilon_{ij}\right)X_j(k)\\ &= \left[\frac{1}{2}\beta_{ij} + \alpha_{ij}\cdot\varepsilon_{ij} + \gamma_{ij}\right]X_i(k) + \left[\alpha_{ij}\left(1-\varepsilon_{ij}\right) + \frac{1}{2}\beta_{ij}\right]X_j(k)\\ &= \left[\frac{1}{2}\beta_{ij} + \alpha_{ij}\cdot\varepsilon_{ij} + (1-\beta_{ij} - \alpha_{ij})\right]X_i(k) + \left[\alpha_{ij}\left(1-\varepsilon_{ij}\right) + \frac{1}{2}\beta_{ij}\right]X_j(k)\\ &= \left[1-\left(\alpha_{ij}\left(1-\varepsilon_{ij}\right) + \frac{1}{2}\beta_{ij}\right)\right]X_i(k) + \left[\alpha_{ij}\left(1-\varepsilon_{ij}\right) + \frac{1}{2}\beta_{ij}\right]X_j(k)\end{aligned}$$

Let $\omega_{ij} = \left(1-\varepsilon_{ij}\right)\alpha_{ij} + \frac{1}{2}\beta_{ij}$. Given the equation above, we observe that ω_{ij} is the expected weight agent i gives to the attitude of agent j. We then arrive at a concise expression for the expected attitude of agent i, given that agents i and j meet.

$$\mathbf{E}[X_i(k+1)|\boldsymbol{X}(k)] = \left(1-\omega_{ij}\right)\cdot X_i(k) + \left(\omega_{ij}\right)\cdot X_j(k)$$

In our model, conditioned on the same two agents selected, the resulting effect on each agent's attitude is the same regardless of which agent is selected first to initiate the interaction.

From here, we assume that the above equation exactly captures the dynamic of attitudes for agent i when meeting agent j, i.e., given that agents i and j meet (regardless of order),

$$X_i(k+1) = \left(1-\omega_{ij}\right)\cdot X_i(k) + \left(\omega_{ij}\right)\cdot X_j(k)$$

We further assume every agent in V has a uniform probability of initiating an interaction, such that $\mathbf{P}$ (an agent initiates an interaction)$= \frac{1}{n}$. Therefore, with probability $\frac{1}{n}(p_{ij} + p_{ji})$, the following attitude dynamic (written in terms of the expected weights ω_{ij} and ω_{ji} for each pair of agents $i, j \in V$) occurs:

$$\begin{cases} X_i(k+1) = \left(1-\omega_{ij}\right)\cdot X_i(k) + \left(\omega_{ij}\right)\cdot X_j(k) \\ X_j(k+1) = \left(1-\omega_{ji}\right)\cdot X_j(k) + \left(\omega_{ji}\right)\cdot X_i(k) \\ X_k(k+1) = X_k(k) \ \forall\, k \neq i, j \end{cases} \tag{3.4}$$

The conditional value of agent i's attitude at the next interaction is a function of not only the probabilities where agent i elects others to interact with ($p_{ij}\ \forall\, j{:}\, p_{ij} > 0$), but also the probabilities where all other agents can select agent i to interact with ($p_{ji}\ \forall\, j{:}\, p_{ji} > 0$).

Let us examine more closely how agent i's attitude changes when interacting with agent j.

$$X_i(k+1) = (1-\omega_{ij}) \cdot X_i(k) + (\omega_{ij}) \cdot X_j(k)$$
$$= X_i(k) - (\omega_{ij}) \cdot X_i(k) + (\omega_{ij}) \cdot X_j(k)$$

Writing the dynamic this way illustrates that agent i's attitude at the next interaction is equivalent to his own *full* attitude at the previous interaction, plus the weighted attitude of agent j at the previous interaction, minus his own *weighted* attitude at the previous interaction. Again, note that this dynamic occurs with probability $\frac{1}{n} \cdot (p_{ij} + p_{ji})$.

We can then write the expected value of agent i's attitude at interaction k+1 over the possible interactions it initiates or is subject to by the others' initiation, conditioned on every agents' attitude at the previous interaction k.

$$\mathbf{E}[X_i(k+1)|\boldsymbol{X}(k)] = X_i(k) + \sum_j \frac{1}{n} \cdot p_{ij} \cdot \omega_{ij} \cdot X_j(k) - \sum_j \frac{1}{n} \cdot p_{ij} \cdot \omega_{ij} \cdot X_i(k)$$
$$+ \sum_j \frac{1}{n} \cdot p_{ji} \cdot \omega_{ij} \cdot X_j(k) - \sum_j \frac{1}{n} \cdot p_{ji} \cdot \omega_{ij} \cdot X_i(k)$$

Next we combine the like terms of $X_i(k)$ and $X_j(k)$, as well as factor out $X_i(k)$ because we recognize that it is not affected by summing over j.

$$\mathbf{E}[X_i(k+1)|\boldsymbol{X}(k)] = X_i(k) + \frac{1}{n} \cdot \sum_j [p_{ij} \cdot \omega_{ij} \cdot X_j(k) + p_{ji} \cdot \omega_{ij} \cdot X_j(k)]$$
$$- \frac{1}{n} \cdot X_i(k) \cdot \sum_j (p_{ij} \cdot \omega_{ij} + p_{ji} \cdot \omega_{ij})$$
$$\mathbf{E}[X_i(k+1)|\boldsymbol{X}(k)] = X_i(k) + \frac{1}{n} \cdot \sum_j [(p_{ij} \cdot \omega_{ij} + p_{ji} \cdot \omega_{ij}) \cdot X_j(k)]$$
$$- \frac{1}{n} \cdot X_i(k) \cdot \sum_j (p_{ij} \cdot \omega_{ij} + p_{ji} \cdot \omega_{ij})$$

We now desire to succinctly express the expected attitude of all agents at interaction k+1, conditioned on all the agents' previous attitudes. This step draws on both the law of iterated expectations and the linearity of expectations. First, we simply take the expression $\mathbf{E}[X_i(k+1)|\boldsymbol{X}(k)]$ and assemble a vector of all entries for each i:

$$\mathbf{E}[\boldsymbol{X}(k+1)|\boldsymbol{X}(k)] = \boldsymbol{X}(k) + Q \cdot \boldsymbol{X}(k)$$

Where each component of the matrix $Q \in \mathbb{R}^{|V|\times|V|}$ is defined as

$$Q_{ij} = \begin{cases} \frac{1}{n} \cdot (p_{ij} \cdot \omega_{ij} + p_{ji} \cdot \omega_{ij}), & i \in \mathcal{A}, j \in V \text{ and } i \neq j \\ -\frac{1}{n} \cdot \sum_j (p_{ij} \cdot \omega_{ij} + p_{ji} \cdot \omega_{ij}), & i \in \mathcal{A}, j \in V \text{ and } i = j \\ 0, & i \in S, \forall j \in V \end{cases} \tag{3.5}$$

Then we take the expected value of this vector and use the linearity of expectations.

$$\mathbf{E}\big[\mathbf{E}[\boldsymbol{X}(k+1)|\boldsymbol{X}(k)]\big] = \mathbf{E}[\boldsymbol{X}(k+1)] = \mathbf{E}[\boldsymbol{X}(k)] + Q \cdot \mathbf{E}[\boldsymbol{X}(k)]$$

For ease of notation, let $\mu_{\boldsymbol{X}}(k) \in \mathbb{R}^{n\times 1}$ be the vector of the expected value of $\boldsymbol{X}(k)$, i.e. $\mu_{\boldsymbol{X}}(k) = \mathbf{E}[\boldsymbol{X}(k)]$. Therefore,

$$\mu_{\boldsymbol{X}}(k+1) = \mu_{\boldsymbol{X}}(k) + Q \cdot \mu_{\boldsymbol{X}}(k) \tag{3.6}$$

This discrete dynamical system captures the expected change in attitudes of all agents from interaction k to k+1. In this work, we are interested in the long-term behavior of this system. Future work involves analyzing it for shorter time horizons.

To solve this system of equations at steady state, we consider when $k \to \infty$ such that:

$$\mu_{\boldsymbol{X}}(\infty) = \mu_{\boldsymbol{X}}(\infty) + Q \cdot \mu_{\boldsymbol{X}}(\infty) \;\Rightarrow Q \cdot \mu_{\boldsymbol{X}}(\infty) = 0$$

In order to solve this system of equations efficiently, we can decompose the matrix and vector as

$$Q = \begin{bmatrix} A & B \\ 0 & 0 \end{bmatrix} \text{ and } \mu_{\boldsymbol{X}}(\infty) = \begin{bmatrix} \mu_{\boldsymbol{Y}} \\ \mu_{\boldsymbol{Z}} \end{bmatrix}$$

The Q matrix is decomposed into:

1) $A \in \mathbb{R}^{|\mathcal{A}|\times|\mathcal{A}|}$: sub-matrix of the columns of agents $\in \mathcal{A}$, rows of agents $\in \mathcal{A}$
2) $B \in \mathbb{R}^{|\mathcal{A}|\times|S|}$: sub-matrix of the columns of agents $\in S$, rows of agents $\in \mathcal{A}$

The sub-matrix of the columns of agents $\in \mathcal{A}$, rows of agents $\in S$ and the sub-matrix of the columns of agents $\in S$, rows of agents $\in S$ are both 0 because of (3.5).

The $\mu_{\boldsymbol{X}}(\infty)$ vector is decomposed into 2 parts:

1) $\mu_{\boldsymbol{Y}} \in \mathbb{R}^{|\mathcal{A}|\times 1}$: vector of expected long-term attitudes of agents $\in \mathcal{A}$ (mutable agents) at interaction $k \to \infty$.
2) $\mu_{\boldsymbol{Z}} \in \mathbb{R}^{|S|\times 1}$: vector of expected long-term attitudes of agents $\in S$ (immutable agents) at interaction $k \to \infty$. This vector is known because immutable agents in S never change their attitude.

We can then express the dot product of the decomposed system of equations as:

$$A \cdot \mu_{\boldsymbol{Y}} + B \cdot \mu_{\boldsymbol{Z}} = 0 \tag{3.7}$$

$$\Rightarrow \mu_{\boldsymbol{Y}} = A^{-1}(-B \cdot \mu_{\boldsymbol{Z}})$$

Solving for $\mu_{\boldsymbol{Y}}$ yields the vector of expected long-term attitudes for all mutable agents, for a given influence-probabilities on a deterministic social network. Table 3-1 provides a summary of the notation we used in this subsection.

Notation	Description
US	Set of all US agents.
TB	Set of all TB agents.
S	Set of agents who have immutable attitudes, and $S = US \cup TB$.
$\mathcal{A}$	Set of all other agents who have mutable attitudes.
V	Set of nodes in the network. By convention $\|V\| = n$, where n is the number of nodes in the network. Also $V = S \cup \mathcal{A}$.
$X_i(k)$	Agent i's attitude at the k-th interaction, where $X_i(k) \in [-0.5,0.5]$.
p_{ij}	Conditional probability agent i meets agent j, given agent i initiates.
α_{ij}	Interaction-type probability: i is forcefully influenced by j.
β_{ij}	Interaction-type probability: i and j have a regular interaction.
γ_{ij}	Interaction-type probability: i and j have an identity interaction.
ε_{ij}	Self-weight. Fraction of attitude that agent i retains when interacting with agent j, where $\varepsilon_{ij} = [0,1]$
G	Social network, an undirected graph (V, a).
a_{ij}	$a_{ij} = \begin{cases} 1, & \text{if agent } i \text{ connects to agent } j \\ 0, & \text{otherwise} \end{cases}$. We assume symmetric connections such that $a_{ij} = a_{ji}$. Then a is the symmetric $n \times n$ adjacency matrix of graph G.
$R \subset \mathcal{A}$	Set of *regular* agents, those who exert influence only within their own household.
$F_0 \subset \mathcal{A}$	Set of *forceful$_0$* agents, those who exert influence to within the village (a village leader).
$F_1 \subset \mathcal{A}$	Set of *forceful$_1$* agents, those who exert influence to within the region (a district/regional leader).
$F_2 \subseteq S$	Set of these *forceful$_2$* agents, US and Taliban agents with immutable attitudes.
ω_{ij}	The expected weight agent i gives to the attitude of agent j. Each entry of ω is calculated by $\omega_{ij} = (1 - \varepsilon_{ij}) \cdot \alpha_{ij} + \frac{1}{2} \cdot \beta_{ij}$.
$\boldsymbol{X}(k) \in \mathbb{R}^{n\times 1}$	Vector of random variables for the attitude of all agents at interaction k
$\mu_{\boldsymbol{X}}(k) \in \mathbb{R}^{n\times 1}$	Vector of the expected value of $\boldsymbol{X}(k)$. Equivalently, $\mathbf{E}[\boldsymbol{X}(k)] = \mu_{\boldsymbol{X}}(k)$.
$\mu_{Y,i} \in \mu_{\boldsymbol{Y}}$	Expected attitude of agent i, for $i \in \mathcal{A}$ at interaction $k \to \infty$ (expected long-term attitude). It is an element in the vector $\mu_{\boldsymbol{Y}} \in \mathbb{R}^{\|\mathcal{A}\|\times 1}$ which the expected attitude for all agents in $\mathcal{A}$.
$\mu_{Z,i} \in \mu_{\boldsymbol{Z}}$	Expected attitude of agent i, for $i \in S$ at interaction $k \to \infty$ (expected long-term attitude). It is an element in the vector $\mu_{\boldsymbol{Y}} \in \mathbb{R}^{\|S\|\times 1}$ which the expected attitude for all agents in S.

Table 3-1: Afghan COIN Social Influence Model Notation and Descriptions

3.3.4.2 Implications of the Analytic Result for Optimization

The analytic method of calculating the expected long-term attitudes for all agents is a powerful result. Rather than conducting a Monte Carlo simulation of thousands of interactions, we can now explicitly determine the effect of adjusting agent parameters as well as network connections on the expected long-term attitudes of the entire population. This result gave us a value function for decisions on certain connections, and led us to the optimization formulation which we will discuss in the following section. We also make two important notes. First, this analytic result is for the *long-term* expected attitude (as the number of interactions approaches infinity). Our simulation provided us insight that occasionally agents arrive at these expected long-term attitudes fairly quickly (a result which seemed related to the number of agents in the network, the particular topology, and influence structure). Knowing near-term attitudes after a pre-determined number of interactions may become very useful for 'red-blue' adversarial modeling in a game-theoretic approach. However, we do not consider shorter time horizon effects in this thesis and leave it as future work. Second, this analytic result characterizes the *expectation* of attitudes, and the optimization formulation that follows is for the *expectation* metric. However, the variance of agent attitudes is also clearly a significant consideration in the decision-making process. For example, an optimization formulation that minimizes variance (i.e., stabilizes attitude fluctuations of the agents) may also prove useful and operationally relevant. As with the study of near-term attitudes, we save this for future work.

3.3.5 Network Connections

Having identified the agents and explained their associated properties and behaviors, we now discuss how the agents are connected. In our model, the agents are arranged in a social network where a connection is broadly defined as a relationship between two people that is supported by frequent person-to-person interaction. Recall that we previously defined interactions as any exchange of information or ideas, including discussion, appeals, arguments, threats, or intimidation. We represent the social network as an undirected graph $G = (V, a)$, where V is the set of agents, and a is the symmetric $n \times n$ adjacency matrix of graph G. Note that while we assume that the social network is comprised of undirected edges (the person-to-person interactions occur *between* pairs of agents), we distinguish this idea from the nature of the interactions when clearly persons may transmit unequal amounts of influence along those edges.

In the next section, we discuss a model to rapidly develop hypothetical network connections that are informed by case studies and knowledge of Pashtun society.

3.4 Network Generation Model

In this section, we propose a model that approximates the social interaction network among Pashtun local leaders in a rural Afghan district based upon our understanding of *qawms*, and actors and roles in the society. To understand the network, US counterinsurgents face the dual challenge of identifying both the agents as well as the connections between them. In order to identify the agents (local leaders and Taliban), US soldiers must draw upon an analysis of the operational environment and intelligence gathered during their repeated interactions with the population. While time-consuming and labor-intensive to the counterinsurgent, identifying specific local leaders is the easier of the two challenges because such personalities are public knowledge. More difficult is identifying the interpersonal relationships between the individuals. The reasons for this include 1) the difficulty of detecting person-to-person conversations (absent telephonic or internet-based communication), 2) inaccuracy of self-report data on interactions [81], and 3) the difficulty of coherently assembling and processing the volume of potential information. In order to avoid these difficulties, we first draw upon the principle of homophily[12] ([82], [83], [84]) to generate likely connections (opportunities for social interaction) between agents, and then subsequently allow the US intelligence cells to selectively modify the network based on specific additional information. The homophily-based links between local leaders (listed in the following subsection) are grounded on the characteristics of rural Pashtun society, particularly the strength of *qawms* as well as the geographical isolation of many rural villages. The resulting local leader social network serves as baseline for analysis. The network can further be modified for the presence or absence of specific connections as intelligence reveals, as well as support the probabilistic presence of 'random' connections to others outside the *qawm* (providing us the ability to determine the robustness to missing links). Figure 3-3 depicts the network generation model and its associated inputs and output. We shall discuss each component in further detail.

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[12] Researchers at the US Army Training and Doctrine Command Analysis Center (TRAC) and Naval Postgraduate School (NPS) first applied the principle of homophily in generating network connections in an irregular warfare environment ([84], [109]). Their research was embedded in a more complex agent-based simulation and required the analysis of multiple dimensions of every agent in the network.

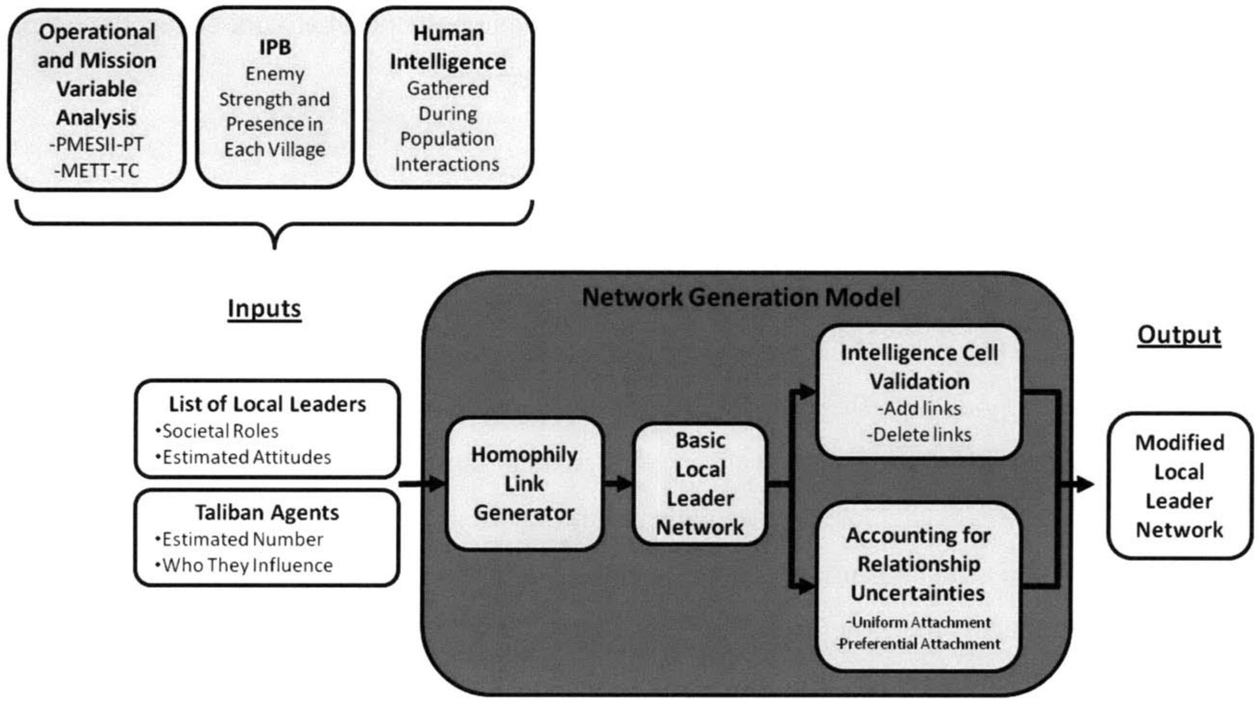

Figure 3-3: Network Generation Model

3.4.1 Inputs

In Sections 2.2 and 2.4.3.2 we discussed the US Army methodology of analyzing the population and the enemy using the operational and mission variables (PMESII-PT and METT-TC) and IPB process, respectively. Additionally, counterinsurgents as part of their daily operations collect human intelligence that feed into subsequent updates of the PMESII-PT and METT-TC variables. Human intelligence, in the form of field notes and patrol debriefs, is collected during the counterinsurgents' interaction with the population during various meetings and engagements. From this collective in-depth analysis, we assume that US counterinsurgents are able to determine for their area of operations the inputs to the network generation model: 1) a list of local leaders that includes the specific roles they fill in the village and district and their estimated attitude, and 2) a list of Taliban agents (number of cells and size) and whom among the population they influence or specifically interact with.

3.4.2 Assumptions

The network generation model is based on several assumptions. First, we assume static edges in our model, which are more reasonable in stable relationships like kinship ties [85] but are not necessarily reasonable for Taliban ties with the population. We acknowledge this shortcoming

and save the modeling of dynamic adversarial connections for future work. We also assume that homophily of roles, *qawm*, and geographical proximity can be a fairly accurate predictor of connections between different Pashtun local leaders. Homophily, while it is a well studied phenomenon in among some groups [82], has not yet been rigorously applied to Afghans.

3.4.3 Homophily Link Generator

Identifying the interpersonal connections among different local leaders is obviously difficult. We use the principle of homophily, that "contact between similar people occurs at a higher rate than among dissimilar people" [83], to derive the likely connections between agents. A connection, as defined earlier, is any relationship that supports frequent person-to-person interaction. While there are generally two types of homophily, status (based on major socio-demographic dimensions) and value (based on beliefs) [83], we consider only the former in this work. Based on the strength of *qawms* in rural Pasthun society, we believe that status homophily based an individual's *qawm*, which also likely induces geographical proximity and association with those with a similar role in society, is an appropriate focus. The link generation rules we derived and their justification are in Table 3-2. The rules are not exhaustive of the types of connections that can be formed by *qawms*, but are the more obvious ones based on visible characteristics such as locality and roles in society. The link generator receives the list of agents and subsequently assigns connections among the agents based upon these homophily rules. The resulting network is denoted as $G = (V, a)$, which is a list of agents and a symmetric matrix representing undirected edges.

3.4.4 Intelligence Cell Validation

The homophily link generator assigns probable links between local leaders based upon *qawm,* geographical proximity and role identities. While this is a rapid method of forming an initial social interaction network, it requires validation and correction from soldiers in the intelligence analysis cell. Any of the previous sources of intelligence, including the human intelligence, IPB, and operational and mission variable analysis, may lead the soldiers to identify connections which are not necessarily based upon the specific rules listed. For example, a Soldier may discover that a particular head of household in a village is related to the district chief of police and that they often interact. While obtaining such pieces of intelligence about relationships between villagers is common, networks created solely from such information would likely be

very sparse. Augmenting an existing homophily-based interaction network with specific connections provides a more complete network.

#	Rule	Justification/Supporting Sources
1	A head of household has a connection with every other head of household in the village.	Small number of heads of households in every village. Sedentary rural communities and geographical proximity and shared kinship [29].
2	A *malik* has a connection with every head of household (and *jirga* member) in the village	He is the public authority in the village, and is often even selected by the village *jirga* [39].
3	A *malik* has a connection with the district sub-governor	He is the representative of the village to the district leadership. The sub-governor holds regular meetings with them ([39], [34]).
4	A *malik* has a connection with the district police chief	He is the representative of the village to the district leadership ([39], [34]).
5	A *malik* has a connection with the every other *malik* of the neighboring village (same village cluster)	Sedentary rural communities and geographical proximity and shared kinship [29].
6	A *mullah* has a connection with every head of household (and *jirga* member) in the village	Prominence of the mullah, the mosque, and religion in daily life. ([42], [86], [34], [41]) Mullahs provide attend and bless the *jirga* [29].
7	A *mullah* has a connection with the district *ulema*	Some evidence that mullahs communicate with higher level *ulema* [41]
8	A *mullah* has a connection with the *mullah* of the neighboring village (same village cluster)	Some evidence that mullahs have more interactions with neighboring communities [41].
9	A *khan* (sub-tribal leader of a village) has a connection with the *khan* (tribal leader of a village cluster) and the *khan* (sub-tribal leader of a neighboring village)	Sedentary rural communities and geographical proximity. Villages and village clusters and often made up the same kin ([34], [29]).
10	A member of the district *jirga* has a connection with the district sub-governor	District sub-governor has a relationship with district *jirga* to assist in conflict resolution [43].
11	A member of the district *jirga* has a connection with the district *ulema*	Religious clergy attending the higher level *jirgas* are well-known, not local mullahs [29].
12	A member of the district *jirga* has a connection with every other member of the district *jirga*	Members sit in a circle, and interact throughout the meeting [29].
13	A local commander at the village level has a connection with the regional commander (at the district level)	Regional hierarchy of local commanders [33].
14	A local criminal at the village level has a connection with the regional 'crime boss' (at the district level)	Regional hierarchy of some criminal networks [44].

Table 3-2: Homophily Rules Used in the Network Generation Model

3.4.5 Accounting for Random Connections

Even though the link generator and the intelligence cell validation creates a basic topology that is consistent with the sociological data available and informed by specific intelligence, we recognize that it is still an approximation and that (many) links may be absent from the network. In order to effectively capture (and appropriately parameterize) the extent of the missing links, we draw upon a modification of the Watts and Strogatz approach [87] of accounting for randomness of small-world ties in regular networks[13]. In their work, the researchers tried to bridge the gap between regular (lattice) and completely random graphs, both of which were primarily studied at the time but neither of which truly represented real-world networks. They developed a method rewiring links in a regular network with increasing randomness. This rewiring created links which acted as small-world ties. Each existing connection, with some probability determined *a priori*, was rewired to another randomly selected node. The process continued until all connections were considered once. The resulting small-world network exhibited properties known to exist in real-world topologies, namely high clustering[14] and short average path lengths. Figure 3-4 illustrates the effect of rewiring connections by tuning a single parameter [87].

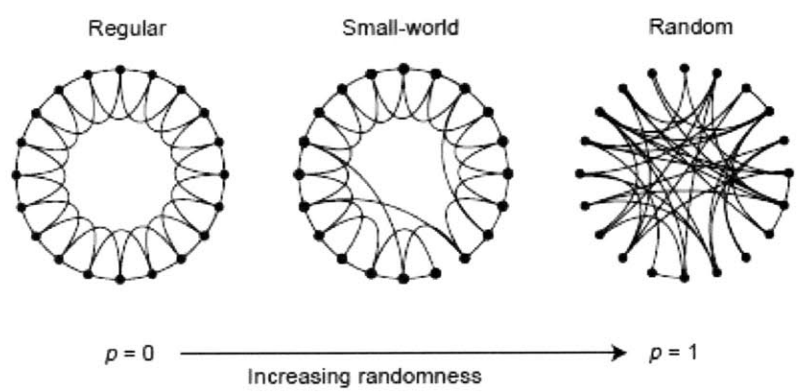

Figure 3-4: Rewiring Procedure [87]

[13] Path length is the distance (as measured by the smallest number of links) between two agents. Small-world ties are those links which cause a large network to have small diameters (longest path length) and small average path lengths [4]. Small average path length is a common characteristic in real-world graphs [4]. Regular networks are those networks in which all nodes have the same degree [4].

[14] Clustering is a naturally occurring network phenomenon where agents, who are commonly connected to the same agent, are also likely to be connected with each other [4].

If we view the topology from our network generating model as analogous to a regular network, then we can similarly add random connections exclusively between villagers (and not with US and Taliban agents) to effectively account for how villagers may have 'small-world' connections with others in the district. In order to determine which agent the rewiring connects with, we explore two different types of network augmenting processes: 1) uniform attachment, and 2) modified preferential attachment [4].

3.4.5.1 Uniform Attachment Process

The uniform attachment process [4] proceeds as follows:

- Select every agent $i \in \mathcal{A}$ once. Recall that $\mathcal{A} = R \cup F_0 \cup F_1$.
- With probability π, agent i forms a connection to some other agent $\in \mathcal{A}$ uniformly in the network. The conditional probability that i connects with any other particular agent is $\rho = \frac{1}{|\mathcal{A}|-1}$.

The parameter π is effectively the uncertainty of the base structure, i.e., the probability that each agent is missing one link. Varying π creates alternative networks that allow us to test the robustness of our models.

3.4.5.2 Modified Preferential Attachment Process

The modified preferential attachment [4] process proceeds as follows:

- Select every agent $i \in \mathcal{A}$ once.
- With probability π, agent i forms a connection to some other agent $\in \mathcal{A}$ in the network. The conditional probability that i connects with an agent whose level of forcefulness is *regular*, *forceful$_0$*, and *forceful$_1$* is ρ_R, ρ_{F_0}, and ρ_{F_1}, respectively, where $0 \leq \rho_R < \rho_{F_0} < \rho_{F_1} \leq 1$, and $\rho_R + \rho_{F_0} + \rho_{F_1} = 1$. Agents within the same level of forcefulness are chosen uniformly at random.

Once again, we use π capture some of the uncertainty we have with the base structure. But instead of an agent connecting uniformly to another agent, we introduce a weighted distribution where an agent is more likely to connect to agents with a greater level of forcefulness. This is similar, but not equivalent, to the pure preferential attachment model where the probability of being connected to is proportional to the degree of the node [4]. This variant of network generation appeals to our intuition that a forceful agent is also more likely to have a greater

number of connections because he is more visible to the public, or more proactive in communication and influence

3.4.6 Output

Our model produces a resulting network that is 1) based on homophily of *qawm*, geographic proximity, and role similarity, 2) modified through human-in-the-loop validation by the intelligence cell, and 3) probabilistically accounts for the presence of random connections among villagers. We believe the model produces a reasonable and informed representation of the interaction network among Pashtun local leaders.

3.5 Nonlethal Targeting Problem

Thus far, we have described both the COIN social influence and network generation models. Further, we have analytically derived a technique to calculate the expected long-term attitudes of the local leaders (mutable agents) given a particular topology as well as a parameterization of the influence-type probabilities. A natural question that follows is what topology produces the attitudes most favorable to the counterinsurgents? More specifically, how should the US agents form connections to other agents in the network that maximizes the favorable attitudes of the population? In this section, we formulate this nonlethal targeting problem as a nonlinear program (NLP). Drawing from the general methodology of the classical static weapon-target assignment (WTA) problem, we seek to find the assignment of a fixed number of US agents to fixed number of local leaders in a social network that maximizes the expected long-term attitudes of the population in favor of the US forces.

3.5.1 Assumptions

In formulating this problem, we make the following key assumptions.

- The social interaction network is known and static. Furthermore, we assume that the network is connected, meaning that there must exist a path of links from every agent to every other agent in the network.
- Each pair of agents' influence-type probabilities is known and fixed.
- The order of interaction (whether agent i initiates an interaction with agent j, or vice versa) has no effect on the outcome of the interaction
- Each agent has a uniform probability of initiating an interaction.

- The number of Taliban agents and their connections to the social network are known and static.
- In this work, we only consider *expected* attitudes as interactions approach infinity (long-term).

3.5.2 Decision Variables--Actions/Controls

We had previously identified a US agent as representative of various US Army organizations who collectively conducted nonlethal activities: the platoon, company, and battalion. Within each of these organizations, there is a leader who serves as the 'face' of the unit to the population (the platoon leader, the company commander, and the battalion commander). However, these organizations also include the soldiers and staff who carry out the missions in support of the leaders. Within each of these organizations are also an increasing amount of resources such as money, equipment, authority. The various endogenous characteristics of each US agent subsequently determine an estimated forceful influence probability.

The number of US agents modeled in the network is dictated by the number of units operating in the area. Based on recent organizational assignments, a battalion typically operates in a province (each with 4-7 districts), a subordinate company operates in 1-2 districts within that province, and its 3-4 subordinate platoons operate within the company boundaries as a whole or further subdivide the district(s) into even smaller sectors.

Given a fixed number of US agents with (possibly) different influence probabilities, the decision one makes is which US agents are assigned to which non-US agents ($j \in \mathcal{A}'$, where $\mathcal{A}' = \mathcal{A} \cup TB$) in the network to connect with. We designate this decision variable as

$$u_{ij} = \begin{cases} 1, & \text{if US Agent } i \text{ connects to agent } j \\ 0, & \text{otherwise} \end{cases}, \text{ where } i \in US,\ j \in \mathcal{A}'$$

The US agents can form a link with either 1) the mutable local leaders, or 2) the immutable Taliban leaders. A link formed between a US agent to any mutable agent in the network (and the subsequent propagation of influence from the US agent to that agent) can be interpreted in various ways including those listed in Section 2.5.1. In practical application, this link can be representative of any activity or communication in which the targeted local leader is frequently reinforced with pro-counterinsurgent attitudes. For example, when US forces single out an individual for nonlethal targeting, it may conduct weekly scheduled meetings with him to discuss

grievances or offer security, resources, and support, as well as initiate a reconstruction project in the targeted individual's village and frequently inspect its progress during friendly visits. All these activities, assuming that they are properly resourced and executed, are designed to shape the local leader's attitude in favor of the counterinsurgent.

A link formed between a US agent and any immutable Taliban agent in the network has a different interpretation. Unlike the local leaders, the assumption is that these ideologically-motivated Taliban agents never change their attitude in favor of the counterinsurgents. Therefore, the US agents are not able to influence Taliban *attitudes* along a link, but are able to alter the *meeting probabilities* with which the Taliban agent negatively influences others. Such a link in this case can be interpreted as conducting any operation in which US agents disrupt the enemy's freedom of movement. For example, US forces might conduct vehicle searches and checkpoints along roads leading into a village and thus interfering with the Taliban efforts to interact with the population.

The number of connections that each US agent makes is pre-determined as well. Each additional connection signifies that the same US agent meets its targets less frequently and therefore is able to influence them less frequently. Because of constrained resources, each US agent should identify a limited number individuals with whom a connection is most beneficial. One of the goals of this work is to help the US agent identify a much more focused set of local leaders to influence.

3.5.3 Derivation of Optimization Formulation

In Section 3.3.4.1, we derived a procedure to analytically calculate the expected long-term attitudes of all agents, given a specific topology of agent connections in a network. We draw heavily upon this procedure to arrive at the subsequent optimization formulation for finding the topology (US agent connections only) that maximizes the weighted expected long-term attitudes of all mutable agents.

Recall equation (3.5), the discrete dynamical system that governs the change in expected attitudes for all agents at each interaction k:

$$\mu_X(k+1) = \mu_X(k) + Q \cdot \mu_X(k)$$

Where each of the components of the matrix $Q \in \mathbb{R}^{|V|\times|V|}$ was defined (3.6) as

$$Q_{ij} = \begin{cases} \frac{1}{n} \cdot (p_{ij} \cdot \omega_{ij} + p_{ji} \cdot \omega_{ij}), & i \in \mathcal{A}, j \in V \text{ and } i \neq j \\ -\frac{1}{n} \cdot \sum_j (p_{ij} \cdot \omega_{ij} + p_{ji} \cdot \omega_{ij}), & i \in \mathcal{A}, j \in V \text{ and } i = j \\ 0, & i \in S, \forall\, j \in V \end{cases}$$

After decomposing the Q matrix and vector μ_X into its parts as described in Section 3.3.4.1, we arrived at the system of linear equations (3.7):

$$A \cdot \mu_Y + B \cdot \mu_Z = 0$$

Both the matrices A and B are dictated by the specific meeting probabilities and weights for each pair of agents, and the vector μ_Z is fixed for the immutable agents $\in S$. In the nonlethal targeting problem, our objective concern is the attitude of the population, μ_Y (expected long-term attitudes for all agents $\in \mathcal{A}$).

3.5.4 Objective Function

While the population's collective favorable attitude is the overall objective in the nonlethal targeting problem, everyone does not necessarily have the same importance to the commander. The unit commander can subjectively determine a weight for each local leader's expected long-term attitude based of a variety of factors including 1) the tactical importance of the village where the local leaders are from, and 2) political factors that may demand that one portion of the population be aligned earlier or in lieu of others. We denote the commander's valuation for the expected long-term attitude of each agent $i \in \mathcal{A}$ as $value_i$, where $value_i \in \mathbb{R}^+$ and $\sum_{i \in \mathcal{A}} value_i = 1$. This is data that is derived by the commander's intent for the population.

We define the objective function in the nonlethal targeting problem: the maximization of the weighted average of the expected long-term attitudes for all mutable agents in the network.

$$\max_u \sum_{i \in \mathcal{A}} value_i \cdot \mu_{Y,i} \tag{3.8}$$

If all the numerical values of $value_i \; \forall\, i \in \mathcal{A}$ were all equivalent, then this objective function reduces to the arithmetic mean of the expected long-term attitudes for all the agents. The particular decisions of who the US agents connect with, u, affect the expected long-term attitude of agent i, $\mu_{Y,i}$, $\forall\, i \in \mathcal{A}$. Having established the objective function, we now turn to the constraints.

3.5.5 Constraints

In order to write the optimization formulation for maximizing the weighted expected long-term attitudes, we must first determine how to express the analytic formulation for μ_Y in terms of the decision variable u_{ij}, which is the assignment of the i-th US agent to the j-th agent $\in \mathcal{A}'$. We allow the US agent to connect with Taliban agents as well, so we expand set $\mathcal{A}$ to $\mathcal{A}' = \mathcal{A} \cup TB$.

The first constraint is derived when we rewrite (3.7) in terms of Q

$$\sum_{j \in \mathcal{A}} (Q_{ij} \cdot \mu_{Y,j}) + \sum_{j \in S} (Q_{ij} \cdot \mu_{Z,j}) = 0, \quad \forall\, i \in \mathcal{A},\ Q \in \mathbb{R}^{|V| \times |V|} \tag{3.9}$$

Next, we proceed to define the terms of Q (3.5) as additional constraints. The simplest one is carrying forward,

$$Q_{ij} = 0, \text{ for } i \in S, \forall j \in V \tag{3.10}$$

For all the other components of Q, we rewrite 1) the meeting probabilities p_{ij} and p_{ji} and 2) the weights ω_{ij} all in terms of the decision variable. We modeled the meeting probabilities as the reciprocal of the number of agents that i or j are connected to, so this process is straightforward. Recall that we defined

$$a_{ij} = \begin{cases} 1, & \text{if agent } i \text{ connects to agent } j \\ 0, & \text{otherwise} \end{cases}.$$

We view these a_{ij}'s as binary data for all agents $i, j \in A'$, meaning that we know which local leaders are connected to each other and which Taliban agents are connected to which local leaders. Additionally, we declare *a priori* the number of connections that the i-th US agent can make and denoted this as $nUSconnect_i, i \in US$. Then we can rewrite the meeting probability p_{ij} as a fraction of the existence of a connection between agents i and j, over the total number of connections that agent i makes with everyone else in the network.

$$p_{ij} = \begin{cases} \dfrac{a_{ij}}{\sum_{k \in \mathcal{A}'} a_{ik} + \sum_{m \in US} u_{mi}}, & i \in \mathcal{A}' \text{ and } j \in \mathcal{A}' \\ \dfrac{u_{ji}}{\sum_{k \in \mathcal{A}'} a_{ik} + \sum_{m \in US} u_{mi}}, & i \in \mathcal{A}' \text{ and } j \in US \\ \dfrac{u_{ij}}{nUSconnect_i}, & i \in US \text{ and } j \in \mathcal{A}' \\ 0, & \text{otherwise} \end{cases}$$

Next, we also rewrite the weights ω_{ij} in terms of the decision variable. Recall that

$$\omega_{ij} = (1 - \varepsilon_{ij}) \cdot \alpha_{ij} + \tfrac{1}{2} \cdot \beta_{ij}, \text{ for } i, j \in \mathcal{A}'$$

Since $\varepsilon_{ij}, \alpha_{ij}, \beta_{ij}$ are all data inputs for $i, j \in \mathcal{A}'$, ω_{ij} is completely deterministic for $i, j \in \mathcal{A}'$. However, there are two other different cases we need to be concerned with. For $i \in \mathcal{A}$ and $j \in US$, we can express the following:

$$\omega_{ij} = u_{ji}\left[(1 - \varepsilon_{ij}) \cdot \alpha_{ij} + \tfrac{1}{2} \cdot \beta_{ij}\right]$$

Multiplying ω_{ij} by the decision variable u_{ji} essentially activates ω_{ij} whenever the j-th US agent connects with the i-th agent. For cases where $j \in US$ we can choose to model a realistic scenario with variability in 1) the effectiveness each US Agent, and 2) the stubbornness of each agent $\in \mathcal{A}$. For every US agent j, let $\beta_{ij} = 0$. Then the probability of the effectiveness of every US Agent j is determined strictly by α_{ij}. Let us assume that this probability is exogenous to the network and the pair-wise connection, and is only based upon the resources, talent, and persuasiveness of the particular US Agent j. Example values of $\alpha_{ij}, j \in US$ are:

Effectiveness	α_{ij}	Logic
Low	.40	Low level of resources
Moderate	.75	Moderate level of resources
High	.90	High level of resources

Table 3-3: Parameters for the Forceful Influence-Type Probability for US Agents

Additionally, we can make the self-weight of an individual with respect with a US agent to be completely *endogenous* to the individual, regardless of the effectiveness of the US agent trying to influence him. Let an agent's self-weight, $\varepsilon_{ij}, j \in US$, be a function of 1) the initial attitude $x_i(0)$, and 2) the level of forcefulness. We parameterize these self-weights in accordance with the following table:

		$\varepsilon_{ij}, j \in US$			
Bin #	$x_i(0)$	regular	Forceful	Forceful$_1$	Forceful$_2$
1	[-0.5, -0.3)	0.30	0.60	0.90	1.00
2	[-0.3, -0.1)	0.23	0.48	0.75	-
3	[-0.1,+0.1]	0.15	0.35	0.60	-
4	(+0.1,+0.3]	0.07	0.23	0.45	-
5	(+0.3,+0.5]	0.00	0.10	0.30	-

Table 3-4: Parameters for the Self-Weight of Non-US Agents to US Agents

This particular set of parameters illustrate the belief that 1) agents who are initially unfavorable to US counterinsurgents have a greater self-weight when interacting with US agents because they are more resistant to US influence, and 2) agents who are more forceful have a greater self-weight when interacting with US agents because they are less susceptible to US influence or require more US effort to influence.

We can rewrite ω_{ij} for $i \in \mathcal{A}$ and $j \in US$:

$$\omega_{ij} = u_{ji}\left[\left(1 - \varepsilon_{ij}\right) \cdot \alpha_{ij} + \tfrac{1}{2} \cdot \beta_{ij}\right]$$

$$= u_{ji}\left[\left(1 - \varepsilon_{ij}\right) \cdot \alpha_{ij}\right]$$

Additionally, for $i \in S$ and $j \in V$, we can express the following because all agents $i \in S$ are stubborn, or immutable.

$$\omega_{ij} = u_{ji}\left[\left(1 - \varepsilon_{ij}\right) \cdot \alpha_{ij} + \tfrac{1}{2} \cdot \beta_{ij}\right] = 0$$

Thus, all associated $\alpha_{ij}, \beta_{ij} = 0$, and $\varepsilon_{ij} = 1$ (because immutable agents are perfectly stubborn and always retain 100% of their belief).

We now have all the pieces to rewrite each of the other components of Q (3.6):

$$Q_{ij} = -\frac{1}{n} \cdot \textstyle\sum_j (p_{ij} \cdot \omega_{ij} + p_{ji} \cdot \omega_{ij}), \text{ where } i \in \mathcal{A}, j \in V \text{ and } i = j$$

$$= -\textstyle\sum_{k \in \mathcal{A}' \setminus i}(Q_{ik}) - \sum_l \left[\frac{1}{n}\left(u_{ji}\left(1 - \varepsilon_{ij}\right) \cdot \alpha_{ij}\right)\left(\frac{u_{li}}{\sum_k a_{ik} + \sum_m u_{mi}} + \frac{u_{li}}{nUSconnect_l}\right)\right], \quad (3.11)$$

$$i = j, \ \forall\, i,j \in \mathcal{A} \text{ (and } k \in \mathcal{A}', \text{ and } m,l \in US)$$

Additionally,

$$Q_{ij} = \frac{1}{n} \cdot (p_{ij} \cdot \omega_{ij} + p_{ji} \cdot \omega_{ij}),$$ where $i \in \mathcal{A}, j \in V$ and $i \neq j$ can be broken into three expressions:

$$Q_{ij} = \frac{1}{n}\left(\omega_{ij}\right)\left(\frac{a_{ij}}{\sum_k a_{ik} + \sum_l u_{li}} + \frac{a_{ji}}{\sum_k a_{jk} + \sum_l u_{lj}}\right), \quad (3.12)$$

$$i \neq j, \forall\, i,j \in \mathcal{A} \text{ (and } k \in \mathcal{A}', l \in US)$$

$$Q_{ij} = \frac{1}{n}\left(u_{ji}\left(1 - \varepsilon_{ij}\right) \cdot \alpha_{ij}\right)\left(\frac{u_{ji}}{\sum_k a_{ik} + \sum_l u_{li}} + \frac{u_{ji}}{nUSconnect_j}\right), \quad (3.13)$$

$$\forall\, i \in \mathcal{A},\ j = US \text{ (and } k \in \mathcal{A}', l \in US)$$

$$Q_{ij} = \frac{1}{n}(\omega_{ij})\left(\frac{a_{ij}}{\sum_k a_{ik} + \sum_l u_{li}} + \frac{a_{ji}}{\sum_k a_{jk} + \sum_l u_{lj}}\right), \qquad (3.14)$$

$$\forall\, i \in \mathcal{A}, \text{and } j = TB \text{ (and } k \in \mathcal{A}', l \in US)$$

For all the other constraints, we justify them below:

$$\sum_{j \in \mathcal{A}'} u_{ij} = nUSconnect_i, \quad \forall\, i \in US \qquad (3.15)$$

$$\mu_{Z,i} = 0.5, \quad \forall\, i \in US \qquad (3.16)$$

$$\mu_{Z,i} = -0.5, \quad \forall\, i \in TB \qquad (3.17)$$

$$u_{ij} = \{0,1\}, \quad \forall\, i \in US, j \in \mathcal{A}' \qquad (3.18)$$

$$-0.5 \le \mu_{Y,i} \le 0.5, \quad \forall\, i \in \mathcal{A} \qquad (3.19)$$

Constraint (3.15) limits the number of connections for the i-th US agent. This limitation may be based off the leader's assessment of his or her ability to reach the local leaders with limited resources. Constraints (3.16) and (3.17) permanently establish the attitudes of both sets of immutable agents (the US and Taliban). Constraint (3.18) declares the decision variable as binary (0,1) between each US agent and all non-US agents in the network (Taliban and local leaders). And lastly, constraint (3.19) limit the range of expected attitudes for all mutable agents between the minimum (-0.5) and the maximum (+0.5) values.

Table 3-5 summarizes the notation we used in this subsection, and Figure 3-5 captures the entire nonlethal targeting problem formulation.

Notation	Description
$value_i$	Commander's value or importance assigned to agent *i*, for $i \in \mathcal{A}$
$nUSconnect_i$	Number of connections that the i-th US agent makes, for $i \in US$
$\mathcal{A}'$	$\mathcal{A} \cup TB$: The union of the set of mutable local leaders and the set of Taliban agents.
u_{ij}	$= \begin{cases} 1, & \text{if US agent } i \text{ connects to agent } j \\ 0, & \text{otherwise} \end{cases}$, where $i \in US,\ j \in \mathcal{A}'$ (binary decision variable)
$a_{i,j}$	$= \begin{cases} 1, & \text{if agent } i \text{ connects to agent } j \\ 0, & \text{otherwise} \end{cases}$, for $i,j \in \mathcal{A}'$ (adjacency data)
ω_{ij}	$= \left(1 - \varepsilon_{ij}\right) \cdot \alpha_{ij} + \frac{1}{2} \cdot \beta_{ij}$, for $i,j \in \mathcal{A}'$ (weight matrix from data)

Table 3-5: Notation for Optimization Formulation

$alue_i \cdot \mu_{\mathbf{Y},i}$

$_{ij} \cdot \mu_{\mathbf{Y},j}) + \sum_{j \in S}(Q_{ij} \cdot \mu_{\mathbf{Z},j}) = 0$ $\qquad \forall\, i \in \mathcal{A}, \qquad Q \in \mathbb{R}^{|V| \times |V|}$

$\forall\, i \in S$, and $j \in V$

$\cdot \sum_{k \in \mathcal{A}' \setminus i}(Q_{ik}) - \sum_l \left[\frac{1}{n}\left(u_{ji}\left(1 - \varepsilon_{ij}\right) \cdot \alpha_{ij}\right)\left(\frac{u_{li}}{\sum_k a_{ik} + \sum_m u_{mi}} + \frac{u_{li}}{nUSconnect_{\ l}}\right)\right]$ $\qquad i = j$, and $\forall\, i, j \in \mathcal{A}$ (and $h, k \in \mathcal{A}'$; $m, l \in US$

$(\omega_{ij})\left(\frac{a_{ij}}{\sum_k a_{ik} + \sum_l u_{li}} + \frac{a_{ji}}{\sum_k a_{jk} + \sum_l u_{lj}}\right)$ $\qquad i \neq j$, and $\forall\, i, j \in \mathcal{A}$ (and $k \in \mathcal{A}', l \in US$)

$\left(u_{ji}\left(1 - \varepsilon_{ij}\right) \cdot \alpha_{ij}\right)\left(\frac{u_{ji}}{\sum_k a_{ik} + \sum_l u_{li}} + \frac{u_{ji}}{nUSconnect_{\ j}}\right)$ $\qquad \forall\, i \in \mathcal{A}$, and $j = US$ (and $h, k \in \mathcal{A}', l \in US$)

$(\omega_{ij})\left(\frac{a_{ij}}{\sum_k a_{ik} + \sum_l u_{li}} + \frac{a_{ji}}{\sum_k a_{jk} + \sum_l u_{lj}}\right)$ $\qquad \forall\, i \in \mathcal{A}$, and $j = TB$ (and $h, k \in \mathcal{A}', l \in US$)

$_{ij} = nUSconnect_i$ $\qquad \forall\, i \in US$

$.5$ $\qquad \forall\, i \in US$

$\cdot 0.5$ $\qquad \forall\, i \in TB$

$,1\}$ $\qquad \forall\, i \in US, j \in \mathcal{A}'$

$_{\mathbf{Y},i} \leq 0.5$ $\qquad \forall\, i \in \mathcal{A}$

Figure 3-5: Nonlethal Targeting Problem Formulation

While this optimization formulation naturally follows from the analytic expression for the expected long-term attitudes of the population, some of its properties make it difficult to solve exactly. Specifically, the formulation is both nonlinear as well as nonconvex, which requires heuristic methods to solve and often arrives only at local optima. Additionally, there are $O(n^2)$ variables and $O(n^2)$ constraints, where n is the total number of agents in the network, which means the problem is very large. We discuss in the following subsection a simplification to the formulation which significantly reduces the number of variables and constraints.

3.5.6 Simplifying the Formulation

In order to reduce the computational complexity of the problem, we perform a variable substitution:

$$h_i = \sum_k a_{ik} + \sum_l u_{li}, \forall\, i \in \mathcal{A}' \text{ (and } k \in \mathcal{A}', l \in US) \tag{3.20}$$

Due to the connectivity assumption, we also know that $h_i \geq 1$. We can then rewrite the constraints of the optimization formulation in terms of this new variable:

$$Q_{ij} = -\sum_{k \in \mathcal{A}' \setminus i}(Q_{ik}) - \sum_l \left[\frac{1}{n}\left(u_{ji}\left(1-\varepsilon_{ij}\right)\cdot \alpha_{ij}\right)\left(\frac{u_{li}}{h_i} + \frac{u_{li}}{nUSconnect_{\,l}}\right)\right], \quad \forall\, i = j, i, j \in \mathcal{A} \text{ and } l \in US \tag{3.11a}$$

$$Q_{ij} = \frac{1}{n}\left(\omega_{ij}\right)\left(\frac{a_{ij}}{h_i} + \frac{a_{ji}}{h_j}\right), \quad i \neq j, \text{and } \forall\, i, j \in \mathcal{A} \tag{3.12a}$$

$$Q_{ij} = \frac{1}{n}\left(u_{ji}\left(1-\varepsilon_{ij}\right)\cdot \alpha_{ij}\right)\left(\frac{u_{ji}}{h_i} + \frac{u_{ji}}{nUSconnect_{\,j}}\right), \quad \forall\, i \in \mathcal{A}, \text{and } j = US \tag{3.13a}$$

$$Q_{ij} = \frac{1}{n}\left(\omega_{ij}\right)\left(\frac{a_{ij}}{h_i} + \frac{a_{ji}}{h_j}\right), \quad \forall\, i \in \mathcal{A}, \text{and } j = TB \tag{3.14a}$$

Next, we try to remove any fractional terms by writing them with a common denominator. Therefore, we arrive at following:

$$Q_{ij} = -\sum_{k \in \mathcal{A}' \setminus i}(Q_{ik}) - \sum_l \left[\frac{1}{n}\left(u_{ji}\left(1-\varepsilon_{ij}\right)\cdot \alpha_{ij}\right)\left(\frac{u_{li}\cdot nUSconnect_{\,l} + u_{li}\cdot h_i}{h_i \cdot nUSconnect_{\,l}}\right)\right], \quad i = j,\ \forall\, i, j \in \mathcal{A}, \text{and } l \in US \tag{3.11b}$$

$$Q_{ij} = \frac{1}{n}\left(\omega_{ij}\right)\left(\frac{h_j a_{ij} + h_i a_{ji}}{h_i h_j}\right), \quad i \neq j, \text{and } \forall\, i, j \in \mathcal{A} \tag{3.12b}$$

$$Q_{ij} = \frac{1}{n}\left(u_{ji}\left(1-\varepsilon_{ij}\right)\cdot\alpha_{ij}\right)\left(\frac{u_{ji}\cdot nUSconnect_{\ j}+u_{ji}\cdot h_i}{h_i\cdot nUSconnect_{\ j}}\right),\ \forall\, i\in\mathcal{A}, \text{and } j = US \qquad (3.13b)$$

$$Q_{ij} = \frac{1}{n}\left(\omega_{ij}\right)\left(\frac{h_j a_{ij}+h_i a_{ji}}{h_i h_j}\right),\quad \forall\, i\in\mathcal{A}, \text{and } j = TB \qquad (3.14b)$$

Now the next step is to rewrite constraint (3.9) by substituting in (3.12b), (3.13b), and (3.14b):

$$\sum_{j\in\mathcal{A}}\left(Q_{ij}\cdot\mu_{\mathbf{Y},j}\right)+\sum_{j\in S}\left(Q_{ij}\cdot\mu_{\mathbf{Z},j}\right)=0,\quad \forall\, i\in\mathcal{A}$$

$$\Rightarrow \sum_{j\in\mathcal{A}\setminus i=j}\left[\frac{1}{n}\left(\omega_{ij}\right)\left(\frac{h_j a_{ij}+h_i a_{ji}}{h_i h_j}\right)\cdot\mu_{\mathbf{Y},j}\right]+\left(Q_{ij}\cdot\mu_{\mathbf{Y},j}\right)\Big|_{i=j}$$

$$+\sum_{j\in TB}\left[\frac{1}{n}\left(\omega_{ij}\right)\left(\frac{h_j a_{ij}+h_i a_{ji}}{h_i h_j}\right)\cdot\mu_{\mathbf{Z},j}\right]$$

$$+\sum_{j\in US}\left[\frac{1}{n}\left(u_{ji}\left(1-\varepsilon_{ij}\right)\cdot\alpha_{ij}\right)\left(\frac{u_{ji}\cdot nUSconnect_{\ j}+u_{ji}\cdot h_i}{h_i\cdot nUSconnect_{\ j}}\right)\cdot\mu_{\mathbf{Z},j}\right]=0$$

Because of the complexity of cases where $i = j, \forall\, i \in \mathcal{A}, j \in V$, we examine it more closely:

$$\left(Q_{ij}\cdot\mu_{\mathbf{Y},j}\right)\Big|_{i=j} = -\sum_{k\in\mathcal{A}'\setminus i=j}\left[Q_{ik}\cdot\mu_{\mathbf{Y},j}\right]$$

$$-\sum_{l\in US}\left[\frac{1}{n}\left(u_{ji}\left(1-\varepsilon_{ij}\right)\cdot\alpha_{ij}\right)\left(\frac{u_{li}\cdot nUSconnect_{\ l}+u_{li}\cdot h_i}{h_i\cdot nUSconnect_{\ l}}\right)\cdot\mu_{\mathbf{Y},j}\right]$$

$$= -\sum_{k\in\mathcal{A}\setminus i=j}\left[Q_{ik}\cdot\mu_{\mathbf{Y},j}\right]-\sum_{k\in TB}\left[Q_{ik}\cdot\mu_{\mathbf{Y},j}\right]$$

$$-\sum_{l\in US}\left[\frac{1}{n}\left(u_{ji}\left(1-\varepsilon_{ij}\right)\cdot\alpha_{ij}\right)\left(\frac{u_{li}\cdot nUSconnect_{\ l}+u_{li}\cdot h_i}{h_i\cdot nUSconnect_{\ l}}\right)\cdot\mu_{\mathbf{Y},j}\right]$$

$$= -\sum_{k\in\mathcal{A}\setminus i=j}\left[\frac{1}{n}\left(\omega_{ik}\right)\left(\frac{h_k a_{ik}+h_i a_{ki}}{h_i h_k}\right)\cdot\mu_{\mathbf{Y},j}\right]-\sum_{k\in TB}\left[\frac{1}{n}\left(\omega_{ik}\right)\left(\frac{h_k a_{ik}+h_i a_{ki}}{h_i h_k}\right)\cdot\mu_{\mathbf{Y},j}\right]$$

$$-\sum_{l\in US}\left[\frac{1}{n}\left(u_{ji}\left(1-\varepsilon_{ij}\right)\cdot\alpha_{ij}\right)\left(\frac{u_{li}\cdot nUSconnect_{\ l}+u_{li}\cdot h_i}{h_i\cdot nUSconnect_{\ l}}\right)\cdot\mu_{\mathbf{Y},j}\right]$$

Putting this latter expression back into the constraint (3.9) and re-indexing gives us:

$$\sum_{j\in\mathcal{A}\setminus i=j}\left[\frac{1}{n}\left(\omega_{ij}\right)\left(\frac{h_j a_{ij}+h_i a_{ji}}{h_i h_j}\right)\cdot\mu_{\mathbf{Y},j}\right]-\sum_{j\in\mathcal{A}\setminus i=j}\left[\frac{1}{n}\left(\omega_{ik}\right)\left(\frac{h_k a_{ik}+h_i a_{ki}}{h_i h_k}\right)\cdot\mu_{\mathbf{Y},i}\right]$$

$$-\sum_{j\in TB}\left[\frac{1}{n}\left(\omega_{ik}\right)\left(\frac{h_k a_{ik}+h_i a_{ki}}{h_i h_k}\right)\cdot\mu_{\mathbf{Y},i}\right]-\sum_{j\in US}\left[\frac{1}{n}\left(u_{ji}\left(1-\varepsilon_{ij}\right)\cdot\alpha_{ij}\right)\left(\frac{u_{li}\cdot nUSconnect_{\ l}+u_{li}\cdot h_i}{h_i\cdot nUSconnect_{\ l}}\right)\cdot\mu_{\mathbf{Y},i}\right]$$

$$+\sum_{j\in TB}\left[\frac{1}{n}\left(\omega_{ij}\right)\left(\frac{h_j a_{ij}+h_i a_{ji}}{h_i h_j}\right)\cdot\mu_{\mathbf{Z},j}\right]+\sum_{j\in US}\left[\frac{1}{n}\left(u_{ji}\left(1-\varepsilon_{ij}\right)\cdot\alpha_{ij}\right)\left(\frac{u_{ji}\cdot nUSconnect_{\ j}+u_{ji}\cdot h_i}{h_i\cdot nUSconnect_{\ j}}\right)\cdot\mu_{\mathbf{Z},j}\right]$$

$$=0$$

We combine terms defined over the same indices:

$$\sum_{j\in\mathcal{A}\setminus i=j}\left[\frac{1}{n}\left(\omega_{ij}\right)\left(\frac{h_j a_{ij}+h_i a_{ji}}{h_i h_j}\right)\cdot\left(\mu_{\mathbf{Y},j}-\mu_{\mathbf{Y},i}\right)\right]+\sum_{j\in TB}\left[\frac{1}{n}\left(\omega_{ij}\right)\left(\frac{h_j a_{ij}+h_i a_{ji}}{h_i h_j}\right)\cdot\left(\mu_{\mathbf{Z},j}-\mu_{\mathbf{Y},i}\right)\right]$$

$$+\sum_{j\in US}\left[\frac{1}{n}\left(u_{ji}\left(1-\varepsilon_{ij}\right)\cdot\alpha_{ij}\right)\left(\frac{u_{ji}\cdot nUSconnect_{\ j}+u_{ji}\cdot h_i}{h_i\cdot nUSconnect_{\ j}}\right)\cdot\left(\mu_{\mathbf{Z},j}-\mu_{\mathbf{Y},i}\right)\right]=0$$

We now write this equation with a common denominator, carefully noting that there is really a different constant for $nUSconnect_j$ in the denominator for each $j \in US$. For our particular parameterization, however, we can assume that $nUSconnect_j = C$ for $\forall\, j \in US$. This means that we solve the problem for which all US agents can connect to the same number of agents.

$$\sum_{j\in\mathcal{A}'} u_{ij} = C,\ \forall\, i \in US \tag{3.15a}$$

Also, we define $h_j = C,\ \forall\, j \in US$. This is because h_j is really the total number of connections that agent j has with other agents in the network, and we fix the number of connections that agent $j \in US$ can make.

$$\sum_{j\in\mathcal{A}\setminus i=j}\left[\frac{1}{n}\left(\omega_{ij}\right)(C)\left(\frac{h_j a_{ij}+h_i a_{ji}}{h_i h_j\cdot C}\right)\cdot\left(\mu_{\mathbf{Y},j}-\mu_{\mathbf{Y},i}\right)\right]$$
$$+\sum_{j\in TB}\left[\frac{1}{n}\left(\omega_{ij}\right)(C)\left(\frac{h_j a_{ij}+h_i a_{ji}}{h_i h_j\cdot C}\right)\cdot\left(\mu_{\mathbf{Z},j}-\mu_{\mathbf{Y},i}\right)\right]$$
$$+\sum_{j\in US}\left[\frac{1}{n}\left(u_{ji}\left(1-\varepsilon_{ij}\right)\cdot\alpha_{ij}\right)(C)\left(\frac{u_{ji}\cdot C+u_{ji}\cdot h_i}{h_i C\cdot C}\right)\cdot\left(\mu_{\mathbf{Z},j}-\mu_{\mathbf{Y},i}\right)\right]=0$$

Dividing through by C and h_i we get the new constraint in formulation which replaces (3.11b), (3.12b), (3.13b), and (3.14b):

$$\begin{aligned}&\sum_{j\in\mathcal{A}\setminus i=j}\left[\left(\omega_{ij}\right)\left(\frac{h_j a_{ij}+h_i a_{ji}}{h_j}\right)\cdot\left(\mu_{\mathbf{Y},j}-\mu_{\mathbf{Y},i}\right)\right]\\&+\sum_{j\in TB}\left[\left(\omega_{ij}\right)\left(\frac{h_j a_{ij}+h_i a_{ji}}{h_j}\right)\cdot\left(\mu_{\mathbf{Z},j}-\mu_{\mathbf{Y},i}\right)\right]\\&+\sum_{j\in US}\left[\left(u_{ji}\left(1-\varepsilon_{ij}\right)\cdot\alpha_{ij}\right)\left(\frac{u_{ji}\cdot C+u_{ji}\cdot h_i}{C}\right)\cdot\left(\mu_{\mathbf{Z},j}-\mu_{\mathbf{Y},i}\right)\right]=0\end{aligned} \tag{3.9c}$$

The primary benefit of this new formulation is that the computational complexity is greatly reduced. While the problem is still nonlinear and nonconvex, there are only $O(n)$ variables and $O(n)$ constraints, where n is the total number of agents in the network. Figure 3-6 captures the revised nonlethal targeting problem formulation.

$$\sum_{i\in\mathcal{A}} value_i \cdot \mu_{\mathbf{Y},i}$$

$$_{\in\mathcal{A}\setminus i=j}\left[(\omega_{ij})\left(\frac{h_j a_{ij}+h_i a_{ji}}{h_j}\right)\cdot(\mu_{\mathbf{Y},j}-\mu_{\mathbf{Y},i})\right]+\sum_{j\in TB}\left[(\omega_{ij})\left(\frac{h_j a_{ij}+h_i a_{ji}}{h_j}\right)\cdot(\mu_{\mathbf{Z},j}-\mu_{\mathbf{Y},i})\right] \qquad \forall\, i\in\mathcal{A}$$

$$-\sum_{j\in US}\left[(u_{ji}(1-\varepsilon_{ij})\cdot\alpha_{ij})\left(\frac{u_{ji}\cdot C+u_{ji}\cdot h_i}{C}\right)\cdot(\mu_{\mathbf{Z},j}-\mu_{\mathbf{Y},i})\right]=0$$

$$_i=\sum_k a_{ik}+\sum_l u_{li} \qquad \forall\, i\in\mathcal{A}' \text{ (and } k\in\mathcal{A}', l\in US)$$

$$_i\geq 1 \qquad \forall\, i\in\mathcal{A}' \text{ (and } k\in\mathcal{A}', l\in US)$$

$$_{j\in\mathcal{A}'} u_{ij} = C \qquad \forall\, i\in US$$

$$_{\mathbf{Z},i}=0.5 \qquad \forall\, i\in US$$

$$_{\mathbf{Z},i}=-0.5 \qquad \forall\, i\in TB$$

$$_{ij}=\{0,1\} \qquad \forall\, i\in US, j\in\mathcal{A}'$$

$$0.5\leq\mu_{\mathbf{Y},i}\leq 0.5 \qquad \forall\, i\in\mathcal{A}$$

Figure 3-6: Revised Nonlethal Targeting Problem Formulation

4 Experiments and Analysis

In this chapter we describe the design, implementation and analysis of experiments that demonstrate how our modeling approach can assist with the nonlethal targeting problem. Experiment I analyzes the capabilities of the optimization formulation in terms of size of the network it can handle, the number of US agents and connections it can prescribe on the network, and the associated computation time. Experiment II analyzes the performance of the optimization by validating its solution with a complete enumeration of the possible connections on limited cases using both small and large networks. Lastly, Experiment III analyzes the operational performance of the nonlethal targeting model by comparing its simulated and analytically calculated expected long-term attitudes with random (control) and doctrine-based methods of target selection. It shows the value of our modeling approach and also reveals some operational insights gained by using our models to assist with nonlethal targeting in COIN.

4.1 Implementation

Before describing each of the experiments, we briefly explain the implementation of the models. All programs and experiments were run on a personal computer with an ©AMD Athlon™ 64 X2 2.91 GHz Dual Core Processor, and 2.00 GB of RAM.

4.1.1 Agent Database

We produced an agent database file in ©Microsoft Excel 2007, which allows users to specify 1) the local leaders in their area of operations, 2) the roles in society that those leaders fill, 3) the estimated attitude of each local leader, 4) the value assigned to each local leader, and 5) the number of Taliban agents present and their suspected connections to the local leaders. An example of this file is included in Appendix B. We believe that our choice of Excel for the database interface is appropriate because of its familiarity and availability among US Army leaders and intelligence specialists, as well as its ease of manipulation.

4.1.2 Network Generator

We implemented the network generator in ©MATLAB, Version R2008A. The software can read the agent data from the Excel file, generate the social interaction network data according to the homophily rules and specified S2-directed connections, and produce a visual representation

of the network. This latter step requires the automated arrangement of nodes to make large networks more visually appealing. In order to create such an organization of nodes, we relied on the use of the Kamada-Kwai force-directed drawing algorithm [88] found in ©Pajek, Version 1.08. The network generator in MATLAB exported the adjacency matrix into a format readable by Pajek. The adjacency matrix was manually imported into Pajek, which arranged the nodes according to the algorithm, and exported x-y coordinates for each node. This list of coordinates was then manually imported back into MATLAB in order to complete the visualization function. Since we chose to work with one large network, we only had to perform this process once.

4.1.3 Monte Carlo Simulation

We implemented the Monte Carlo simulation in MATLAB in order to analyze the attitude dynamics of the population according to the Afghan COIN social influence model on the topologies created from the network generation model. A Monte Carlo simulation is a technique of replicating the probabilistic behavior of a system with the aid of computers [89]. MATLAB simulated the dynamics at each interaction by randomly selecting an agent, selecting a neighbor of that agent, and adjusting the attitudes of the pair of agents according to the interaction-type probabilities. This process was performed over a specified number of interactions.

4.1.4 Optimization with AMPL and KNITRO

The nonlethal targeting model was coded in ©AMPL, Version 20100122, and solved using the commercial nonlinear solver ©KNITRO, Version 6.0.0 by Ziena Optimization, Inc. The data for this implementation was manually imported into an AMPL data file from a MATLAB-generated Excel file.

KNITRO [90] is a commercial solver designed to handle a wide range of optimization problems, including mixed-integer, nonlinear problems (MINLP). However, since our problem contained nonconvex constraints, it was difficult to solve it to true optimality. The default setting in KNITRO was to return the first locally optimal solution. However, KNITRO also offered a multi-start heuristic to find a set of local optima, the best of which has the greatest chance of being closest to the global optimum. In this multi-start heuristic, KNITRO by default generated $\max(200, 10n)$ number of start points, where n is the number of variables in the problem. The solver generated a start point by randomly selecting feasible values for each component of the

decision variable (satisfying the upper and lower bounds of each component). The solver then found a local optimum for each start point generated. The targeting assignment that the solver returned, therefore, was simply the best of the local optima but was still not guaranteed to be the global optimum.

KNITRO uses a branch and bound algorithm to solve MINLPs. This algorithm involves partitioning the feasible set of integer solutions, and solving the sub-problems defined by those sets of solutions (hence the term 'branch'). Additionally, this algorithm assumes our ability to 1) efficiently compute upper bounds (in the case of maximization) often through the relaxation of integrality constraints, and 2) occasionally solve a sub-problem to optimality and thus obtaining an incumbent lower bound. This algorithm saves time by ignoring sub-problems whose upper bound is less than the current feasible solution (hence the term 'bound') [91].

4.2 Network Data and Other Parameters

In order to avoid any potential security or other issues, we constructed two fictional datasets of Afghan agents, roles, and attitudes. While fictional, these datasets were based upon our study and knowledge of Pashtun society, and loosely correlated with publically available aggregate data on Pashtun districts ([92], [93], [94]). See Appendix B for more information. We determined two reasonable sets of agents to study in our experiments: one with 16 local leaders and another with 73 local leaders. Recall that *local leaders* as those individuals within the population who by virtue of their authority, power, or position have influence over the attitudes of a group of people (see Section 2.6.1.2). The number of Taliban and US agents were exogenous to these initial setups. We will discuss both of the networks generated by our network generation model in more detail in the following sub-sections.

Interestingly, the topologies created from our network generation model were similar to the structures generated from the *islands model*, which is an economic model of network formation developed by Jackson ([4], [95]). Essentially the model captures the process by which agents form connections with other agents based upon the connection costs. The model posits that connections within one's own 'island' (or closer neighbors) is strictly less costly than connections with those outside the island, and that only a few agents with enough social capital can afford these latter connections. While we do not explicitly discuss the economics of how Pashtun local leaders form connections with others, we believe that this concept is implicitly

embedded in the principle of homophily. Although certainly not without exception, we see rural Pashtun villagers more likely forming local connections than with distant ones.

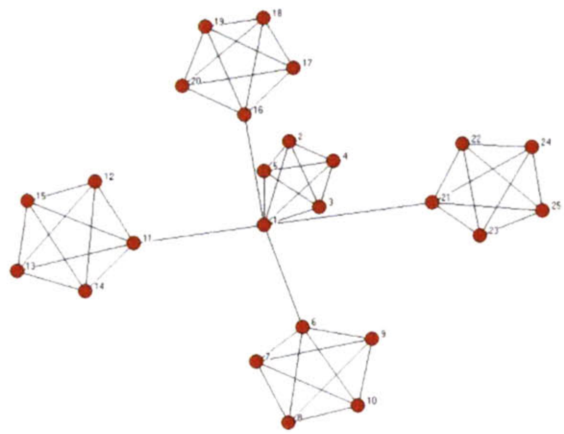

Figure 4-1: A sample network generated from the 'islands' economic model [95]

4.2.1 A Small Network

We first developed a small 16-node network that is a representative sub-graph of a more realistic social interaction network. We used this smaller network for initial model development, testing, and analysis. The list of agents used to generate the 16 node network is shown in Table 4-1.

Node #	Village	Societal Position	Forcefulness Level	Initial Attitude
1	-	District Sub-governor	forceful$_1$	-0.3
2	A	Village *Malik*	forceful	-0.3
3	A	Head of Household	regular	0.0
4	A	Head of Household	regular	0.0
5	A	Head of Household	regular	0.0
6	A	Head of Household	regular	0.0
7	B	Village *Malik*	forceful	0.3
8	B	Head of Household	regular	0.0
9	B	Head of Household	regular	0.0
10	B	Head of Household	regular	0.0
11	B	Head of Household	regular	0.0
12	C	Village *Malik*	forceful	0.3
13	C	Head of Household	regular	0.0
14	C	Head of Household	regular	0.0
15	C	Head of Household	regular	0.0
16	C	Head of Household	regular	0.0

Table 4-1: Agent List and Characteristics in Small Network

Note that this table includes information that the network generation model required in order to create a topology, including: village, societal position, and initial attitude. Observe also that this list contains local leaders in three villages, notionally named A, B, and C. Within each village were four heads of household and one village *malik* (executive). Furthermore, a sub-governor of the district presided over these three villages. The network generator received this data and formed links between agents based upon the homophily rules previously described in Table 3-2.

Additionally, we added 2 links for hypothetically-known relations beyond our homophily rules shown in Table 4-2. This step is analogous to the intelligence analyst adding links to the network based on credible information as discussed in Section 3.4.4.

#	**Undirected Links**		**Description**
1	7	12	Village B *Malik* to village C *Malik*
2	2	7	Village A *Malik* to village B *Malik*

Table 4-2: Intelligence-informed Connections in Small Network

Additionally, based upon an agent's societal position, the network generator assigned a forcefulness level and the appropriate influence-type probabilities for that level (which were determined *a priori*). We also note the initial attitude states of the agents: all the regular agents had a neutral attitude, two forceful agents had a positive attitude (0.3), and both a forceful and forcefull agent had a negative attitude (-0.3) towards the counterinsurgents. Lastly, the network generator also provided a pictorial representation of the network as shown in Figure 4-2 according to the legend in Figure 4-3.

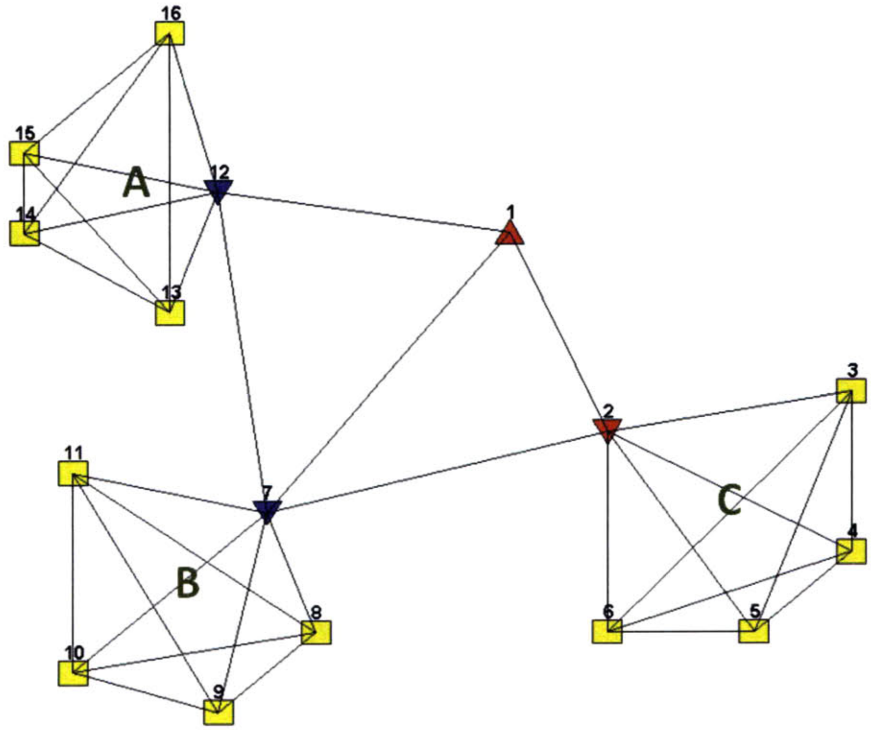

Figure 4-2: A Small Network

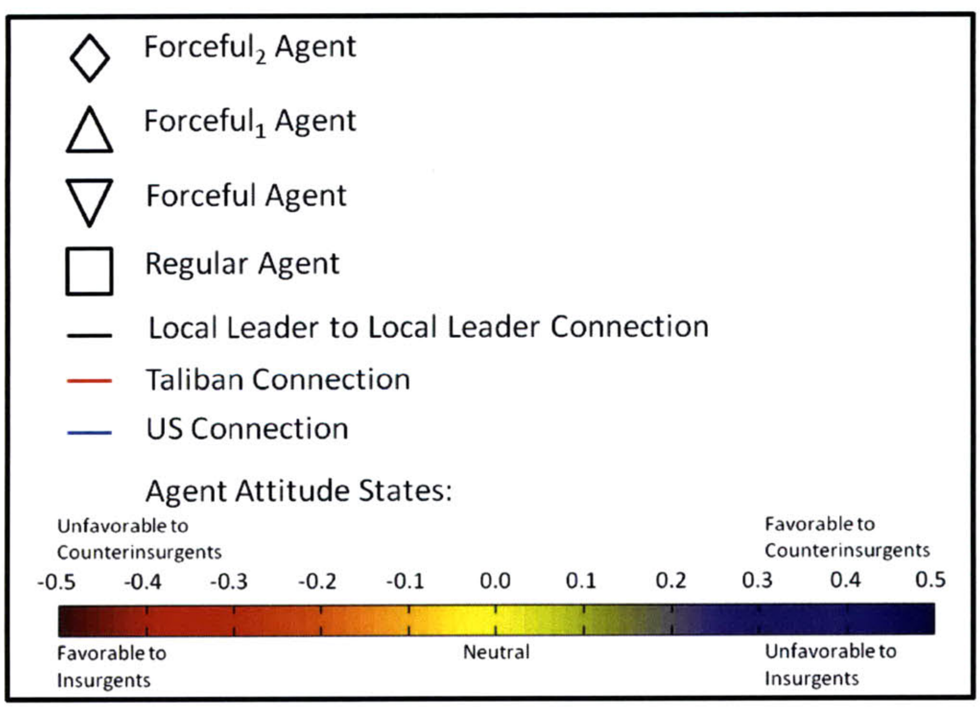

Figure 4-3: Legend for Network Generator Graphs

4.2.2 A Large Network

We then developed a network that is a more realistic representation of a rural Pashtun district by increasing the number of agents to a larger proportion of the sizes found in two real datasets (see Appendix B), and including more types of local leaders found in Pashtun society. This larger network consisted of 73 nodes, and is depicted below in Figure 4-4.

The complete list of agents is given in Appendix B. Note that this network consisted of several district-level authorities as well as 7 principal villages (labeled A through G), each of which included heads of households and village leaders. Additionally, we assigned initial attitudes of the population generally by village, reflecting the common observation that villages collectively exhibit clear friendliness, unfriendliness, or neutrality towards US forces [15]. Lastly, note that this network was constructed almost entirely by homophily from the network generation model. Only 15 links were added that were not covered by the homophily rules in our model (see the list of links in Appendix B). These links were additional connections to the local and regional criminals, as well as to the regional warlord and district police chief. As with the small network, this later step is analogous to the intelligence analyst (S2) adding links to the network based on credible information.

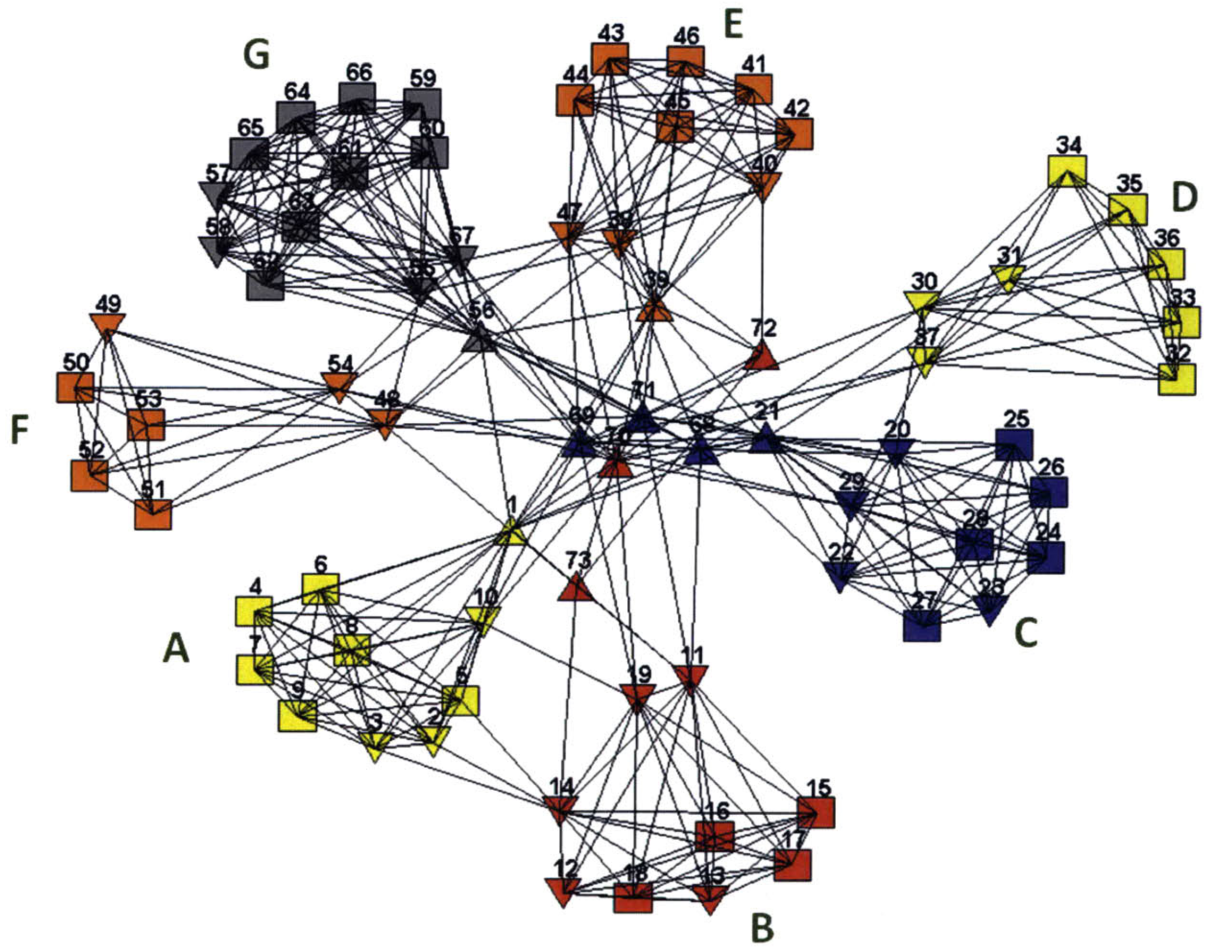

Figure 4-4: A Large Network

4.3 Experiment 1

The ultimate goal of Experiment 1 was to estimate the network sizes as well as the number of US agents and respective connections that our model can reasonably handle (in terms of runtime) to maximally increase the expected long-term attitudes of the population. In order to do this, we experiment with 1) changes to the multi-start settings for the KNITRO solver, and 2) fixing the decision variables of connections between US agents to regular agents to 0. Both of these modifications are explained in more detail below.

As explained earlier in this chapter, the KNITRO solver we chose offered a multi-start option that increases the likelihood of finding a better local optimum for a given problem. This feature can be enabled for the default number of start points, enabled to a different number of start

points, or disabled altogether. Obviously, the more start points that the solver uses the more likely it is to find a solution closer to the global optimum but also the greater amount of time it takes to obtain a solution. While we desired a solution to the nonlethal targeting problem that is close to optimum (maximally increases the arithmetic mean of the expected long-term attitude of the population), we did not require it to be globally optimal. We qualified our goal as such because we recognized that possible enemy counteractions (such as changing its connections to certain people) would dampen or change the expected attitudes we are trying to maximize before they ever reached their value as the number of interactions approached infinity. However, we also desired to obtain a good locally optimal solution quickly and identified the trade-off between potentially better solutions and runtimes. Accordingly, in this experiment, we wished to determine comparative runtimes and performance of the nonlethal targeting optimization model for various cases of the multi-start settings, as well as to analyze the effect of increasing network size on runtimes.

Additionally, we modified the formulation of the revised nonlethal targeting problem (NLTP) in order to reduce computation time. In preliminary testing, we observed that the model never assigned connections from US agents to regular agents if the number of connections was fewer than the number of forceful and forceful$_1$ agents. This is intuitively obvious because regular agents, as parameterized, have the lowest level of influence. They represent the local leaders whose influence does not extend beyond the household and immediate neighbors (who are also heads of household). If the objective was to simply increase the arithmetic mean of the expected long-term attitude of the entire population, connections with forceful agents are more effective because such connections subsequently propagate to more agents in the network. As such, we decided that we can better constrain the set of feasible solutions to the nonlethal targeting problem by fixing all the binary decision variables of connections from US agents to regular agents to 0. Equivalently, we added the following constraint to the NLTP formulation:

$$u_{ij} = 0 \qquad \forall\, i \in R, j \in US \tag{3.21}$$

We will refer to this revised formulation as NLTP1.

Throughout all of Experiment 1, we configured the problem according to the default parameterization shown in Section 3.3.3.1. Specifically, we set $\alpha_{ij} = 1$, and $\beta_{ij} = 0$ for $i \in \mathcal{A}'$ and $j \in US$ (which is the highest level of forcefulness) and $\varepsilon_{ij} = \varepsilon_{US} = 0$ (the same for all

agents that the US agents connected to). This particular modeling parameterization made the US agents as forceful as the Taliban agents.

Additionally, we conducted Experiment 1 on both small and large networks. The small network we used is the same one described in Section 4.2.1. The large network we used was same as the one described in Section 4.2.2, except that it did not include the intelligence-directed connections. It therefore had the same number of nodes, the same types of nodes, and the same homophily-derived connections.

We subdivided Experiment 1 into 3 separate experiments. Experiment 1A analyzed runtimes on both small and large networks on the NLTP formulation when KNITRO multi-start was enabled to the default number of start points. Experiment 1B analyzed the comparative runtimes and performance on both small and large networks on both the NLTP and NLTP1 formulations for various multi-start settings. And finally, Experiment 1C focused on determining runtimes for even larger networks using only the NLTP1 formulation and multi-start disabled. A summary of these experiments is shown below in Table 4-3.

Experiment	Multi-Start Setting	Formulation	Purpose
1A	Enabled, default number of start points	NLTP	Analyze runtimes of NLTP for small and large networks and an increasing number of US agents and connections.
1B	Varied	NLTP and NLTP1	Compare runtimes and performance of the 2 formulations for different multi-start settings on the same networks
1C	Disabled	NLTP1	Analyze runtimes of NLTP1 for larger networks and various numbers of US agents and connections.

Table 4-3: Summary of Experiment 1

4.3.1 Experiment 1A

4.3.1.1 Design

In Experiment 1A, we analyzed runtimes of the revised nonlethal targeting formulation, NLTP, as shown in Figure 3-6, Our expressed purpose was determining how runtimes with multi-start enabled in all cases were affected by 1) changes in the size of the network, 2) changes in number of US agents, and 3) changes in the number of connections those US agents are allowed to make.

For each case within the experiment, we varied these properties and solved for the US connections that maximally increased the expected long-term attitude.

Throughout this experiment, we used the NLTP formulation. Additionally, we used KNITRO's default number of start points, $\max(200, 10n)$, where n is the number of variables in the problem. The topologies (local leader and Taliban connections) remained fixed for cases 1-8, 9-12, and 13-15. The only variations we made within those cases were the number of US agents and connections to assign. The topologies used for the 3 sets of cases are shown in the Appendix B.

4.3.1.2 Results and Analysis

The summary table of results of Experiment 1A is shown in Table 4-4. The table records: 1) the network configuration, 2) the corresponding number of nodes visited (branch points in the branch and bound algorithm), and 3) the runtimes to arrive at a solution.

Case #	Number of local leaders	Number of TB agents	Number of US agents	Connections per US agent	Nodes Visited	Runtime (in secs.)
1	16	1	1	1	3	10.289
2	16	1	1	3	3	10.212
3	16	1	3	1	23	138.705
4	16	1	3	3	2	15.922
5	16	1	3	5	2	13.788
6	16	1	5	1	11	142.063
7	16	1	5	3	11	123.822
8	16	1	5	5	2	20.812
9	16	3	3	1	2	17.798
10	16	3	3	3	15	94.601
11	16	3	3	5	29	164.162
12	16	3	5	5	23	201.781
13	73	3	1	1	17	1210.499
14	73	3	2	1	181	15246.169
15	73	3	3	3	-	> 50400

Table 4-4: Experiment 1A Results

We observed that with multi-start enabled, runtimes for a large network and moderate numbers of US agents and connections (cases #14-15) can become very large. KNITRO found a locally optimal solution for 2 US agents and 1 connection for the large network only after more than 4 hours of computation time. It could not find a solution for 3 US agents and 3 connections after 14 hours. See Appendix B for the complete table of results.

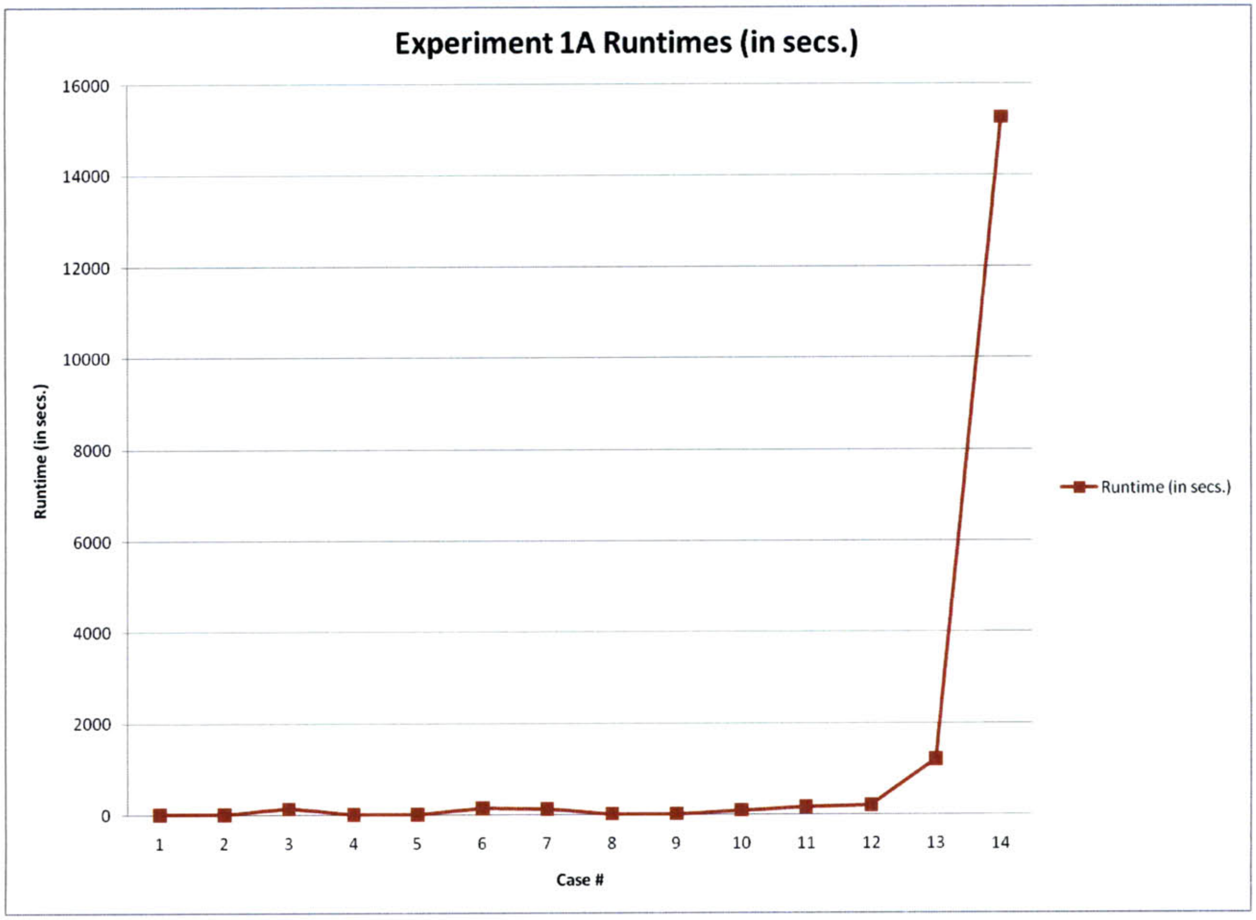

Figure 4-5: Plot of Experiment 1A Runtimes by Case Number

Figure 4-5 depicts the dramatic increase in runtimes for cases 12-14, which involved an increasing number of US agents and connections on the large network. We concluded that while enabling multi-start to the default number of starting points seems to be a useful feature to find very good local optima, it caused a significant increase in computation time for the large network and a moderate number of US agents and connections.

4.3.2 Experiment 1B

4.3.2.1 Design

In Experiment 1B, we analyzed runtimes and performance of both NLTP and NLTP1 across a range of multi-start settings, network sizes, and network topologies. The goal here was to determine whether using the NLTP1 formulation and/or enabling multi-start for a fewer number

of start points would noticeably affect the quality of the local optima obtained or the runtime it to obtain it.

Because the NLTP1 formulation precluded US agent targeting assignments to regular agents, we note upfront the number of regular agents in the test topologies. For the 16- and 73-node networks, there were 12 and 38 regular agents, respectively, who were not considered for US agent connections.

We divided Experiment 1B into two different parts. In Part 1, we compared the performance and runtimes between the NLTP and NLTP1 formulations when multi-start is enabled to the default number of start points. In this part, we selected the identical case conditions from cases 1, 3, 6, and 13 in Experiment 1A. In those case conditions, we compared previously obtained results from Experiment 1A (using the NLTP formulation) with those obtained using the NLTP1 formulation where we fixed binary decision variables of US to regular agents to 0. In Part 2, we varied the multi-start settings using only the NLTP1 formulation and compared performance and runtimes.

4.3.2.2 Results and Analysis

In Part 1 of Experiment 1B, we observed that there are generally small differences in performance between NLTP and NLTP1. In each case listed in Table 4-5, the NLTP1 formulation always obtained the same target assignment as NLTP but in roughly a third of the runtime. The first number of the case number label signifies identical test parameters with the associated Experiment 1A case. The "B1" label signifies that the case belongs to Part "1" of Experiment 1-"B". See Appendix B0 for the complete table of results.

Case #	Number of local leaders	Number of Regulars	Number of TB agents	Number of US agents	Connect-ions per US agent	Nodes Visited	Runtime (in secs.)	% Deviation from NLTP OBJ	% Deviation from NLTP Runtime
1-B1	16	12	1	1	1	3	3.503	0	34.0
3-B1	16	12	1	3	1	21	49.703	0	35.8
6-B1	16	12	1	5	1	11	35.726	0	25.1
13-B1	73	38	3	1	1	17	397.79	-0.00027	32.9
14-B1	73	38	3	2	1	129	4374.327	0.00003	28.7

Table 4-5: Experiment 1B, Part 1 Results

Figure 4-6 depicts the differences in runtimes between the NLTP and NLTP1 formulations using the same case configurations 1, 3, 6, 13, and 14.

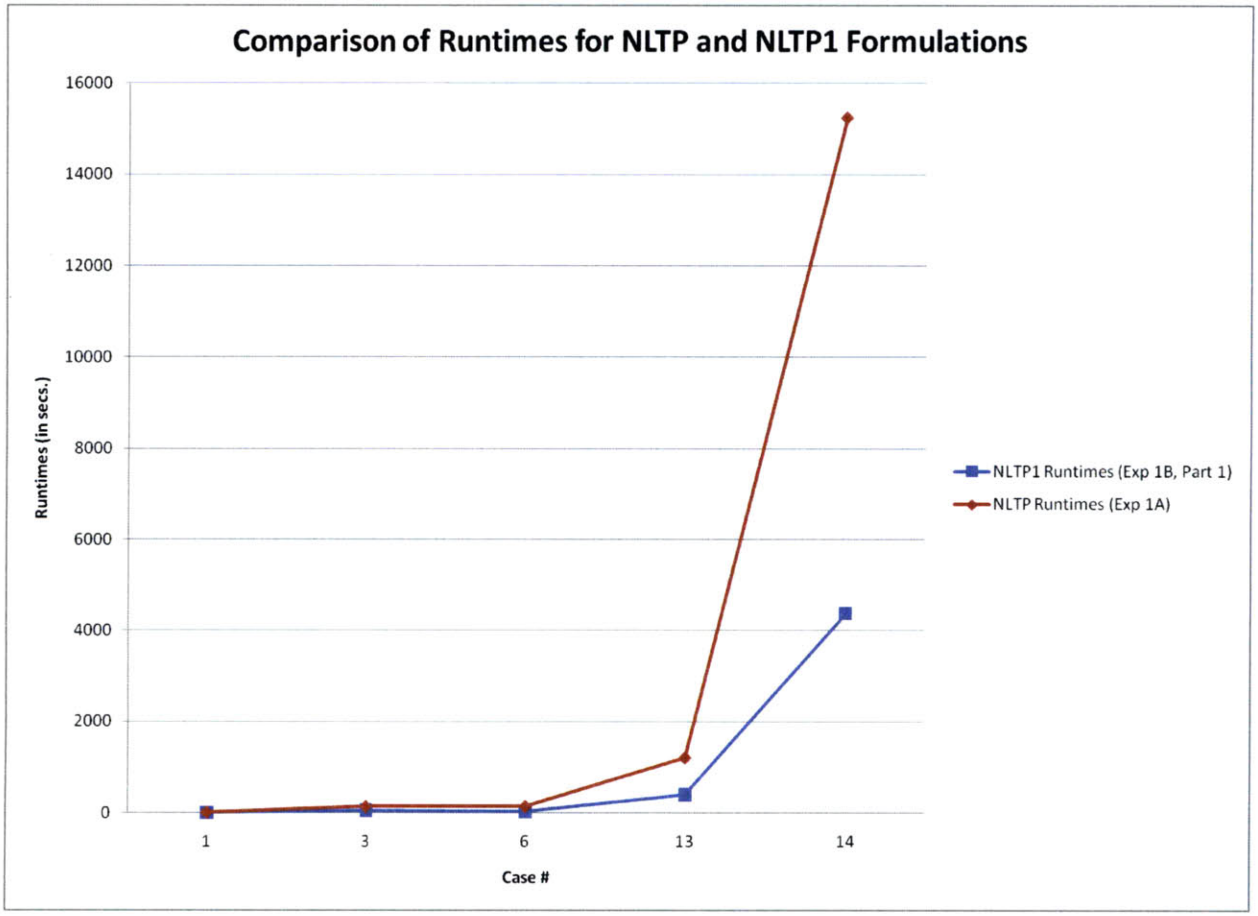

Figure 4-6: Comparison of Runtimes for NLTP and NLTP1 Formulations for Select Case Numbers

In Part 2 of Experiment 1B, we observed that there are in general small differences in performance between various multi-start settings with the NLTP1 formulation, but significant savings in runtime for when multi-start is disabled. The results of this experiment are summarized in Table 4-6, and shown complete in Appendix B. Note that the savings in runtime could not be calculated for cases 15-B2, 16-B2, and 17-B2 because we never ran the corresponding cases for the NLTP formulation due to the projected runtime. Additionally, for those specific cases, we only ran the NLTP1 formulation with multi-start enabled to 10 start points (and not the default due to the project runtimes) and obtained objective values from those runs (denoted with a *).

Case #	Sub-#	Number of local leaders	Number of Regulars	Number of TB agents	Number of US agents	Connect-ions per US agent	Nodes Visited	Runtime (in secs.)	Multi-Start Enabled/ # Points	% Deviation from NLTP1 OBJ	% Deviation from NLTP Runtime
6-B2	1	16	12	1	5	1	7	0.064	N	0.00000	0.045
13-B2	1	73	38	3	1	1	15	176.767	Y/100	0.00002	14.602
13-B2	2	73	38	3	1	1	15	16.481	Y/10	0.00035	1.361
13-B2	3	73	38	3	1	1	13	0.671	N	-0.00046	0.055
14-B2	1	73	38	3	2	1	161	2649.34	Y/100	-0.00014	17.377
14-B2	2	73	38	3	2	1	123	199.238	Y/10	0.00009	1.307
14-B2	3	73	38	3	2	1	31	2.394	N	-0.22088	0.016
15-B2	1	73	38	3	2	2	37	4.514	N	-0.00090*	N/A
16-B2	1	73	38	3	3	1	229	35.979	N	-0.00040*	N/A
17-B2	1	73	38	3	3	3	159	19.985	N	-0.40000*	N/A

Table 4-6: Experiment 1B, Part 2 Results

For various numbers of US agents and connections on both the 16-node and 73-node networks, we tried enabling the multi-start option at 10 or 100 start points (different from the default number) or disabling it altogether. We noticed that for each of the cases, the percent deviation of objective values from multi-start disabled and fully enabled (to a default number of start points) was no more than 0.23% (case 14-B2, sub #3) and often much lower. Additionally, the percent deviation of objective values from multi-start disabled to partially enabled (to 10 start points) was no more than 0.40% (case 17-B2, sub #1). Correspondingly, disabling multi-start allowed us to achieve runtimes that were only several hundredths of a percent of the runtimes from the NLTP formulation. Figure 4-7 depicts the drop in runtimes in cases 13 and 14 by decreasing the use of the multi-start function (using a fewer number of start points) or disabling it altogether. In the figure's legend, "Y" denotes that multi-start was enabled to the default number of start points $\max(200, 10n)$, "Y/100" denotes that multi-start was enabled to 100 start points, and "N" denotes that multi-start was disabled.

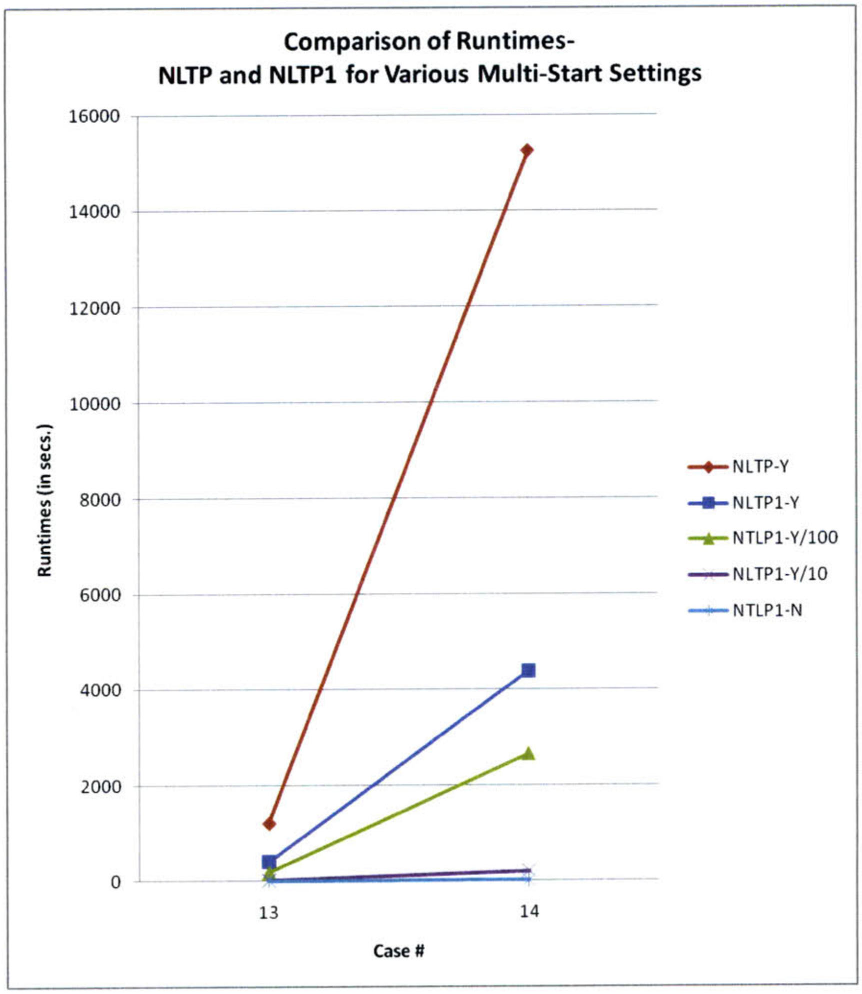

Figure 4-7: Comparison of Runtimes for NLTP and NLTP1 for Various Multi-Start Settings

From Experiment 1B, we concluded that disabling multi-start seems to have a negligible effect on the quality of the local optima obtained while significantly decreasing runtimes.

4.3.3 Experiment 1C

4.3.3.1 Design

From the previous experiment, we concluded that using the NLTP1 formulation and disabling multi-start was an efficient way to proceed. In Experiment 1C we analyzed runtimes under those conditions for even larger networks and connections.

In order to create experimental data for larger networks, we first expanded the 73-node data set by replicating 27 existing agents (in several whole and partial villages) and adding it to the network. This created a 100-node data set. The connections between the agents in this data set

were determined by the network generation model and the homophily-based connection rules within it. No other intelligence-directed connections were added. To create a 200-node data set, we simply duplicated the entire 100-node network. Again, the connections between agents in this data set were determined by strictly by the network generation model. Note that for the 100- and 200-node networks, there were 50 and 100 regular agents, respectively, who were not considered for US agent connections. For cases 18-24 and 25-28, the topologies remained fixed and the only variations were the number of US agents and connections to assign.

4.3.3.2 Results and Analysis

The summary table of results of Experiment 1C is shown in Table 4-7. As before, the table entries include: 1) the network configuration, 2) the corresponding number of nodes visited (branch points in the branch and bound algorithm), and 3) the runtime to arrive at a solution. See Appendix B for the complete table of results.

We observed that runtimes were very sensitive to initial conditions and that for each topology (100- or 200-node) there was not necessarily an increasing relationship between runtimes and the number of US agents or connections to be assigned. Additionally, assigning 10 US agents and 10 connections to the 100-node network took very long (case 24) while assigning the same number or even a larger number of US agents and connections on the 200-node network took significantly less time (cases 27-28). However, despite this dichotomy and based on an overall analysis of the observed runtimes, we believe that our model can likely handle a multitude of additional configurations of networks with 200-nodes or less in reasonable amounts of time.

Case #	Number of local leaders	Number of Regulars	Number of TB agents	Number of US agents	Connections per US agent	Nodes Visited	Runtime (in sec.)
18	100	50	10	5	5	13	8.384
19	100	50	10	5	10	35	19.78
20	100	50	10	7	5	15	10.797
21	100	50	10	7	10	8	5.852
22	100	50	10	9	5	11	8.696
23	100	50	10	9	10	1333	821.586
24	100	50	10	10	10	4846	3175.334
25	200	100	20	5	5	57	53.249
26	200	100	20	5	10	36	45.640
27	200	100	20	10	10	39	85.673
28	200	100	20	20	20	8	36.793

Table 4-7: Experiment 1C Results

4.3.4 Experiment 1 Conclusions

In summary, there are a couple of conclusions we can make from Experiment 1. First, the NLTP1 formulation with multi-start disabled was preferable to NLTP because it often provided negligible differences in target assignment and performance while significantly decreasing runtimes. In fact, we relied on this formulation and the absence of multi-start in order to achieve reasonable runtimes for determining assignments on large networks. Second, provided that we used the NLTP1 formulation with multi-start disabled, we can determine targeting assignments for networks up to 200 agents in size and for up to 20 US agents and 20 connections each in reasonable amounts of time. It is likely that we can solve problems even larger.

4.4 Experiment 2

The goal of Experiment 2 was to compare the performance of nonlethal targeting optimization approach with a complete enumeration of the possible connections for simple configurations of the small and large networks. As stated previously, both versions of the NLTP optimization formulation contained nonconvex constraints and were theoretically very difficult to solve to global optimality. We therefore accepted the likelihood of the KNITRO solver returning locally, but not globally, optimal assignment solutions. However, in this experiment, we wished to examine the performance of the optimization on network configurations where we could explicitly calculate the globally optimal solution through complete enumeration of the solution space.

4.4.1 Experiment 2 Design

In Experiment 2, we compared the performance and runtime of the optimization and enumeration on a number of networks and configurations. For the optimization, we utilized the NLTP1 formulation with multi-start disabled (identical conditions as Experiment 1C). For the enumeration, we made significant use of our analytic result, equation 3.7, to calculate the arithmetic mean of the expected long-term attitudes of the agents for particular network configurations. We wrote a script in MATLAB that receives the topology and parameter inputs as well as the number of US agents and connections allotted to each US agent. The program then proceeded to determine all the possible combinations of connections between US agents and non-US agents (who are the regular, forceful, forceful_1, and Taliban agents) and calculated the

arithmetic mean expected long-term attitude for each combination. The program stored the highest performing combination and reported the overall best as the global maximum after it has enumerated through all possible combinations.

Suppose there were n number of non-US agents, m US agents with k allotted connections. The total number of possible combinations that the program needed to enumerate through to calculate the arithmetic mean of the expected long-term attitude was simply $\binom{n}{k}^m$. This was clearly inefficient, but does allow us to determine the k best connections for each of the m US agents and the globally optimal solution.

In this simple experiment, we standardized the conditions as follows: 1) interaction-type probabilities between agents were fixed according to the default parameterization in Section 3.3.3.1, and 2) all local leaders (non-US and Taliban agents) have equivalent self-weights when interacting with US agents, i.e., $\varepsilon_{ij} = 0$ for $i \in \mathcal{A}'$ and $j \in US$. Additionally, the small and large networks we used in Experiment 2 were the same as the ones used throughout Experiment 1.

4.4.2 Experiment 2 Results and Analysis

We compared the solutions and runtimes between the optimization and enumeration. The complete table of results is shown below in Table 4-8. In all but the last case, the optimization arrived at the same solution and same objective value as the enumeration method in a fraction of the time.

Case #	# Local leaders	# TB agents	# US agents	Connect-ions per US agent	# Possible Combi-nations	MATLAB Enumeration Time (in secs.)	Enumeration Solution	Optimization Solution	NLTP Runtime (in secs.)
1	16	1	1	1	17	6.5156	[1]	[1]	0.061
2	16	1	1	2	136	44.0156	[1,2]	[1,2]	0.031
3	16	1	1	3	680	215.5313	[17,2,1]	[17,2,1]	0.032
4	16	1	2	1	289	105.875	[1],[2]	[1],[2]	0.061
5	73	3	1	1	76	41.6563	[71]	[71]	0.671
6	73	3	1	2	2850	1394.9	[69],[71]	[69],[71]	1.556
7	73	3	1	3	70300	29043	[1 69 71]	[21 69 71]	3.062

Table 4-8: Experiment 2 Results

In case #7, the optimization solution and the enumeration solution differed by one assignment. The enumeration method showed that [1, 69, 71] was the best connection strategy for the single

US agent, resulting in an arithmetic mean expected long-term attitude of 0.14616. The optimization solution reported [21, 69, 71] as the local optimum, resulting in an arithmetic mean expected long-term attitude of 0.13936. The difference was 0.0068 or 0.68% of the range of possible attitudes (over 1.00). One cannot, however, discard the savings in runtime. The enumeration runtime and optimization runtimes differed by nearly 4 orders of magnitude. We also ran the NLTP1 formulation for case #7 with multi-start enabled and arrived at the same solution and objective as the enumeration in 3010.060 seconds.

4.4.3 Experiment 2 Conclusions

This experiment allowed us to compare our locally optimal solutions from NLTP1 to globally optimal solutions obtained by complete enumeration. We observed that the optimization and complete enumeration approaches resulted in identical targeting strategies. In only one case, the optimization returned a slightly inferior assignment strategy but in a much shorter amount of time. While this experiment clearly did not (nor was it intended to) provably show that the optimization approach returned a solution within a small percentage of the globally optimum, it did show that in a few cases the approach's performance was good.

4.5 Experiment 3

The goal of Experiment 3 was to determine the usefulness of our nonlethal targeting assignment approach. We compared our method of nonlethal targeting that utilizes knowledge about the population with US Army doctrine that offers relatively vague principles of selection.

4.5.1 Experiment 3 Design

In Experiment 3, we performed analysis on two different size networks (16- and 73-node) and varied a number of parameters to explore how different methods of assignment selection (control, doctrine, and optimization) performed under the various conditions. We calculated performance both analytically (using equation 3.7) as well as in simulation.

4.5.1.1 Experimental Control

We devised two means of establishing the experimental control. The first was a completely random agent selection among all non-US agents in the network. This essentially represented the completely naïve approach, where every non-US agent had an equal chance of being

assigned as a target for each available connection for each US agent, independent of other assignments. The second type of control was a random agent selection among only forceful, forceful$_l$, and Taliban agents (not among regular or US agents). This modification to randomness reflected the same reasoning used to develop the NLTP1 formulation: regular agents by parameterization influence only a small number of others. Since US connections to such agents are inefficient, a more realistic benchmark for performance was random assignments among those more influential, i.e., the forceful, forceful$_l$ and Taliban agents.

We subsequently divided Experiment 3 into 2 parts based on the size of the network analyzed and the method of experimental control. Analysis in Experiment 3A occurred exclusively on the 16-node network and a completely random control, while analysis in Experiment 3B occurred exclusively on the 73-node network and the modified control (random among non-regular agents). These two parts are summarized in Table 4-9.

Experiment	**Network Size**	**Method of Control**
3A	16-node	Completely Random (among all agents except US)
3B	73-node	Modified Random (among all agents except regular and US)

Table 4-9: Summary of Experiment 3

In portions of Experiment 3, we conducted cases which analyzed the assignment of homogeneous US agents as well as non-homogeneous US agents. Homogeneous US agents all had the same influence-type probabilities. Non-homogeneous US agents had different influence-type probabilities based on resource level as explained in Section 3.5.5. The higher resource level, the higher the probability for forceful influence, α. In particular, we parameterized the resource level of the US agents according to Table 4-10.

Resource Level	α_{ij}
Low (L)	.40
Moderate (M)	.75
High (H)	.90

Table 4-10: Resource Level and Forceful Influence-Type Probability for US Agents

4.5.1.2 Network Topologies and Taliban Connections

The two networks we used in Experiment 3 were precisely the ones described in Sections 4.2.1 and 4.2.2 (i.e., we now utilized the large network with inclusion of the S2-directed connections). For each network, we fixed the Taliban connections *a priori* and show them in red links in the

following figures. For the 16-node network shown below in Figure 4-8, we specifed 3 Taliban agents, each connected to a different local leader.

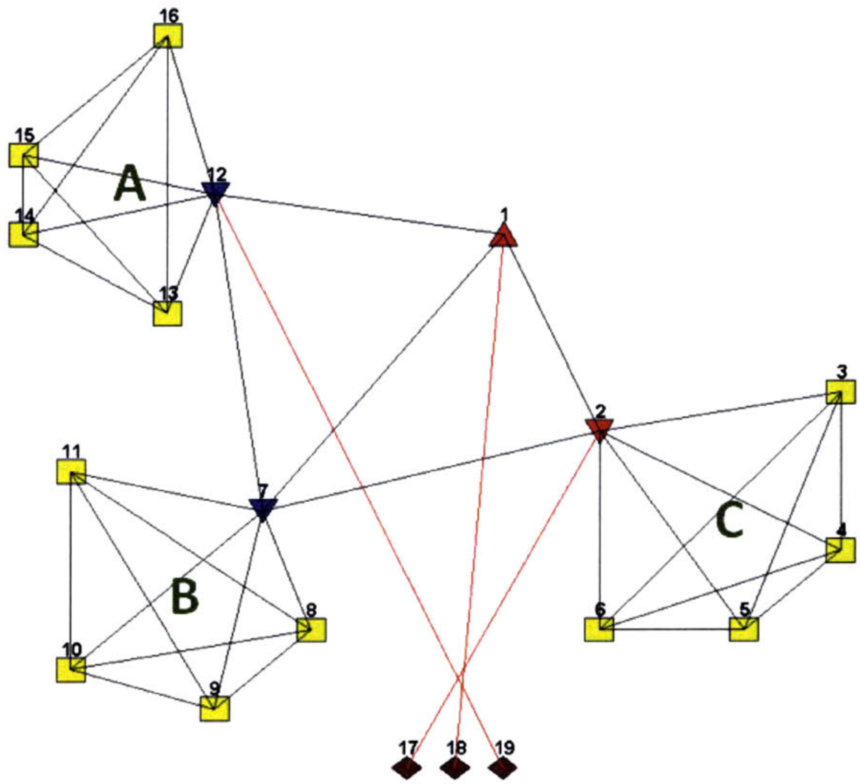

Figure 4-8: Experiment 3 Small Network (with Village Labels)

In the 73-node network shown below in Figure 4-9, we specified 3 Taliban agents as well, however now with 4 connections each.

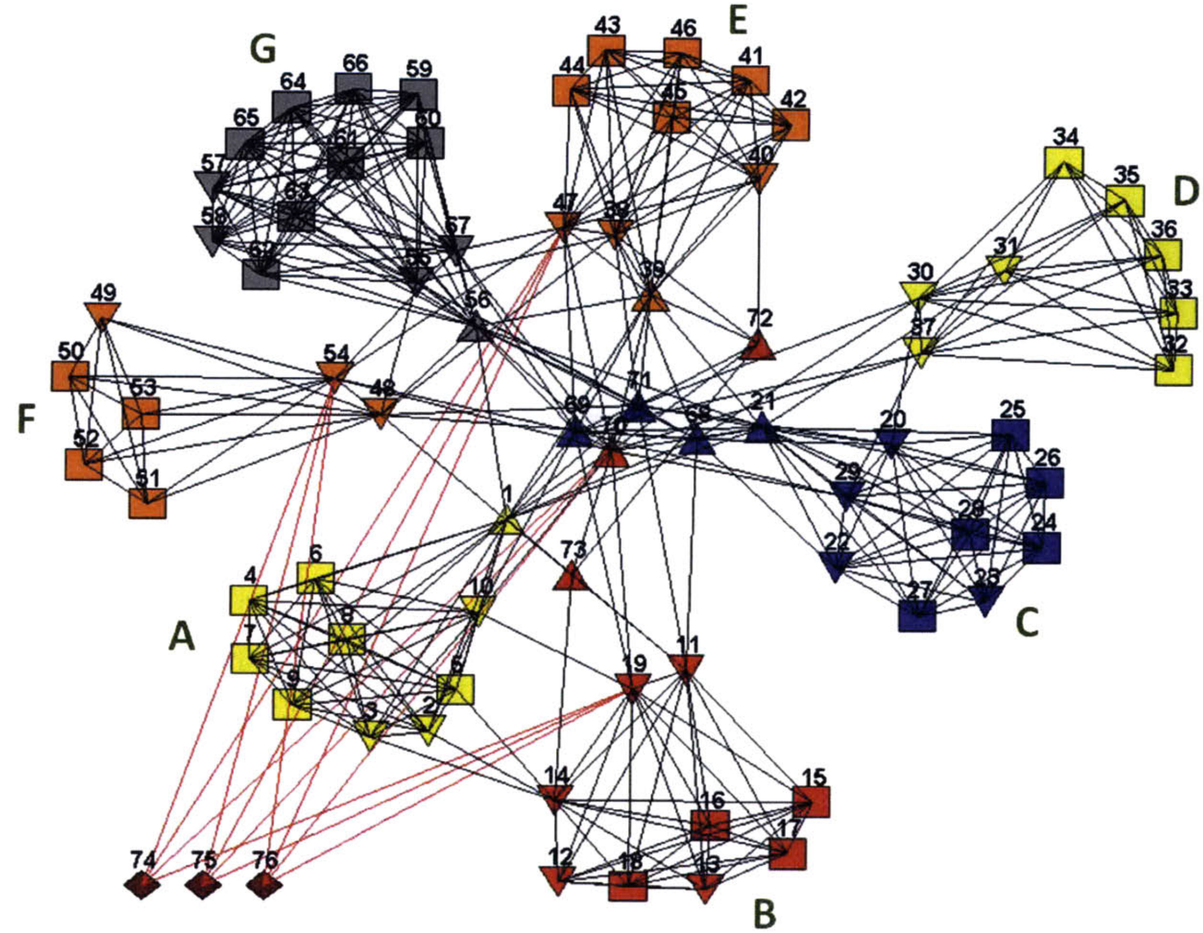

Figure 4-9: Experiment 3 Large Network (with Village Labels)

4.5.1.3 Parameter Adjustments for Cases

While there were many different parameter adjustments that could have been made in this experiment, our cases were comprised of the single and, in some cases, combined applications of the modifications listed below:

- Non-homogeneous US agents and agents with non-homogeneous self-weights when interacting with US agents.
- Forceful interaction-type probability between forceful$_1$ and forceful agents for $\alpha_{ij} = \{0.1, 0.4\}$, where $i \in F_0, j \in F_1$.
- Network uncertainty using uniform attachment with $\pi = \{0.0, 0.5\}$.
- Network uncertainty using preferential attachment with $\pi = \{0.0, 0.5\}$.

The specific modifications for each case for Experiment 3A and 3B are shown in Table 4-11 and Table 4-12, respectively. For the 16-node network, we sought assignments for 3 US agents with 1 connection each. For the 73-node network, we sought assignments for 3 US agents with 3 connections each.

						Adjustments			
Case #	**# local leaders**	**# Regulars**	**# TB agents**	**# US agents**	**Connect-ions per US agent**	**Non-homogeneous US agents and self-weights (Y/N)**	**α between $forceful_1$ to forceful**	**Uniform Attachment (π=)**	**Prefer. Attachment (π=)**
1	16	12	3	3	1	N	0.4	0	0
2	16	12	3	3	1	Y	0.4	0	0
3	16	12	3	3	1	Y	0.1	0	0
4	16	12	3	3	1	Y	0.4	0.5	0
5	16	12	3	3	1	Y	0.4	0	0.5
6	16	12	3	3	1	Y	0.1	0.5	0
7	16	12	3	3	1	Y	0.1	0	0.5
8	16	12	3	3	1	N	0.4	0	0.5

Table 4-11: Table of Cases for Experiment 3A

						Adjustments			
Case #	**# local leaders**	**# Regulars**	**# TB agents**	**# US agents**	**Connect-ions per US agent**	**Non-homogeneous US agents and self-weights (Y/N)**	**α between $forceful_1$ to forceful**	**Uniform Attachment (π=)**	**Prefer. Attachment (π=)**
1	73	38	3	3	3	N	0.4	0	0
2	73	38	3	3	3	Y	0.4	0	0
3	73	38	3	3	3	Y	0.1	0	0
4	73	38	3	3	3	Y	0.4	0.5	0
5	73	38	3	3	3	Y	0.4	0	0.5
6	73	38	3	3	3	Y	0.1	0.5	0
7	73	38	3	3	3	Y	0.1	0	0.5

Table 4-12: Table of Cases for Experiment 3B

Notice that within each experiment 3A and 3B, we fixed the number of local leaders and Taliban agents, as well as the number of US agents and connections. Our intent was to analyze the effect from various case conditions on the performance of the NLTP1 optimization-based selection methods, compared to random (control) and doctrine-based selection methods.

4.5.1.4 Doctrine-Base Selection

In order to determine at the doctrine-selected targets, we drew upon the prescriptions found in the US counterinsurgency field manuals. Current US Army COIN doctrine states the following principles in reference to nonlethal targeting:

- "Identify leaders who influence the people at the local, regional, and national levels"([2]: 5-9).
- Win over "passive or neutral people" ([2]: 5-22)
- "[Nonlethal targets include] people like community leaders and those insurgents who should be engaged through outreach, negotiation, meetings, and other interaction" ([2]: 5-30).
- "Meetings conducted by leaders with key communicators, civilian leaders, or others whose perceptions, decisions, and actions will affect mission accomplishment can be critical to mission success" ([3]: 4-13).
- "Start easy… Don't try to crack the hardest nut first—don't go straight for the main insurgent stronghold, try to provoke a decisive showdown, or focus efforts on villages that support the insurgents. Instead, start from secure areas and work gradually outwards. Do this by extending your influence through the locals' own networks" ([3]: C-5).

Based on such statements from US Army doctrine, we selected targeting assignments for the two networks. The targeting assignments of the non-homogeneous US agents on the small and large networks and the doctrinal justification are explained in Table 4-13 and Table 4-14, respectively. In the case of the homogeneous US agents, we simply considered the set of all assigned targets to be interchangeable among US agents. It is important to note that our selections were based on a particular interpretation of doctrine and accept that there are certainly other valid interpretations which could lead to different targeting assignments. Determining these other assignments and analyzing their performance, however, are tasks in future research.

US Agent		Targeting Assignment			
Agent #	Resource Level	Agent #	Societal Position	Initial Attitude	Doctrinal Justification
20	L	7	Village A *Malik*	+0.3	To win over the most sympathetic local leaders and work to extend US influence through them.
21	M	12	Village B *Malik*	+0.3	To win over the most sympathetic local leaders and work to extend US influence through them.
22	H	1	Sub-governor	- 0.3	Identify local leader at district level to conduct outreach and negotiations.

Table 4-13: Doctrinal Justification of Targeting Assignment in Experiment 3A

US Agent		Targeting Assignment			
Agent #	**Resource Level**	**Agent #**	**Societal Position**	**Initial Attitude**	**Doctrinal Justification**
77	L	21	District *Jirga* Member/*Khan*	+0.3	To win over the most supportive villages and work to extend US influence through them. Village C is the friendliest in the district. Achieving a solid supportive base in Village C might help with winning support in the neighboring Village D. The three most influential community leaders in Village C are the *mullah*, *malik*, and the member of the district *jirga* (who is also from that village and is a tribal *khan*).
		29	Village C *Mullah*	+0.3	
		20	Village C *Malik*	+0.3	
78	M	67	Village G *Mullah*	+0.2	To win over the most supportive villages and work to extend US influence through them. Village G is the next friendliest in the district. Bolstering support in this village might help with winning neighboring Villages E and F. The three most influential community leaders in Village G are the *mullah*, *malik*, and the member of the district *jirga* (who is also from that village). Because immediate neighbors are more unfriendly, this assignment might require a unit with a higher resource level.
		55	Village G *Malik*	+0.2	
		56	District *Jirga* Member	+0.2	
79	H	69	District *Ulema* Member	+0.3	Identify local leaders at district level who can influence all the villages. Build a solid support base among those who are already sympathetic to the US. This assignment deals with individuals who are 'higher-ranking' and may require a unit with the highest resource level.
		71	Sub-governor	+0.3	
		68	District Police Chief	+0.3	

Table 4-14: Doctrinal Justification of Targeting Assignment in Experiment 3B

4.5.1.5 NLTP Optimization Selection

Throughout Experiment 3A, we utilized the NLTP1 formulation with multi-start enabled to the default number of start points. Since the network size was small in Experiment 3A, this did not cost us much in terms of computation time. However, for Experiment 3B conducted on the larger network, we utilized the same formulation but with multi-start disabled. As Experiment 1 demonstrated in many cases, this configuration provided much shorter runtimes and only small losses in performance.

4.5.2 Experiment 3 Results and Analysis

Compared to both the random- and doctrine-based selection methods, we observed that the NLTP1 optimization-based method produced higher mean expected long-term attitudes both analytically and in simulation, on both the small and large networks, in all cases. We analyzed the key results in this subsection but include the complete set of results and analysis in Appendix B.

4.5.2.1 Analytical Performance

Recall that equation 3.7 allowed us to analytically calculate the expected long-term attitude of all agents as the number of interactions approaches infinity. For each case in experiments 3A and 3B, we obtained targeting assignments according to the optimization-based, random, and doctrine-based selection methods. We simply calculated the resulting arithmetic mean of the expected long-term attitudes produced by each selection method for each case. The graphical depiction of this performance for Experiments 3A and 3B is shown in Figure 4-10 and Figure 4-11, respectively.

The results of Experiment 3A showed that optimization out-performed both doctrine-based and random (control) methods of selection. We observed that while the arithmetic mean of the expected long-term attitudes, regardless of the selection method, were predominantly negative (signifying that the arithmetic mean of the expected long-term attitude was against the counterinsurgents), it was important to note how 'less negative' was the mean with optimization-based agent selections. This result showed that in this particular topology and given the specific Taliban presence and existing connections, close to the very best you could do was to influence the population to a mean attitude of around -0.1, which was slightly against the counterinsurgents.

We wished to test for the statistical significance of the performance of the optimization-based selection method over the random or doctrine-based selection methods in Experiment 3A. We declared two null hypotheses: 1) the arithmetic mean of the expected long-term attitudes produced from optimization-based selection and doctrine-based selection across the cases were drawn from identical continuous distributions with equal medians, and 2) the arithmetic mean of the expected long-term attitudes produced from optimization-based selection and random selection across the cases were drawn from identical continuous distributions with equal

medians. We then conducted pair-wise Wilcox Rank Sum (non-parametric) tests on the arithmetic mean of the expected attitudes obtained in Experiment 3A. We discovered that we could not reject the first hypothesis, but could reject the second. With a p-value of 0.1304, which was not significant, we concluded that there was no statistical difference between the means achieved by optimization or by doctrine. However, with a p-value of 0.0001, which was significant, we concluded that the mean expected long-term attitudes obtained by the optimization-based selection method are statistically higher than those obtained by the random (control) method.

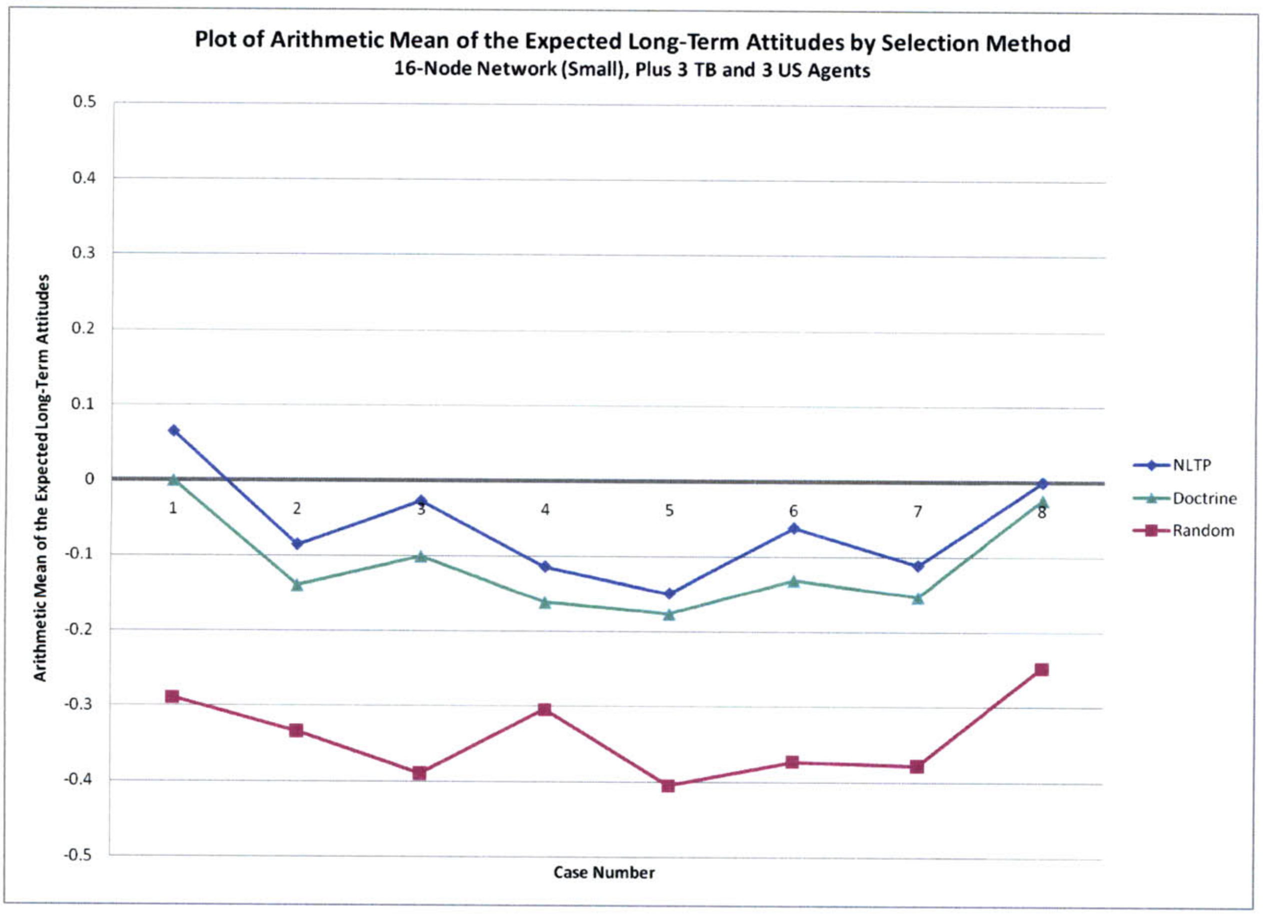

Figure 4-10: Experiment 3A Results-Performance of 3 Selection Methods in 8 Cases

As shown in Figure 4-11, the optimization-based selection method out-performed the random and doctrine-based methods in all cases for Experiment 3B as well. There are two points worthy to note. First, the modified random selection (experimental control) in this experiment performed relatively better than the purely random selection in Experiment 3A. This was

because the modified method selected only among forceful agents (forceful, forceful$_1$, and Taliban agents) rather than both forceful and regular agents. Second, all the mean expected long-term attitudes in Experiment 3B were now positive which signifies only that the Taliban presence was relatively light in this topology rather than any fundamental differences in the selection methods applied to Experiments 3A and 3B (other than the change noted above in the experimental control).

Once again, we wished to measure the statistical significance of these results. We declared the same two null hypotheses except that the cases were now from Experiment 3B. Using the Wilcox Rank Sum test, we obtained p-values of 0.0023 and 0.0041, both of which were significant, for hypotheses 1 and 2, respectively. We concluded that we could reject these null hypotheses and stated that the optimization-based method achieved a statistically significant higher mean expected long-term attitude than both the doctrine-based and random methods.

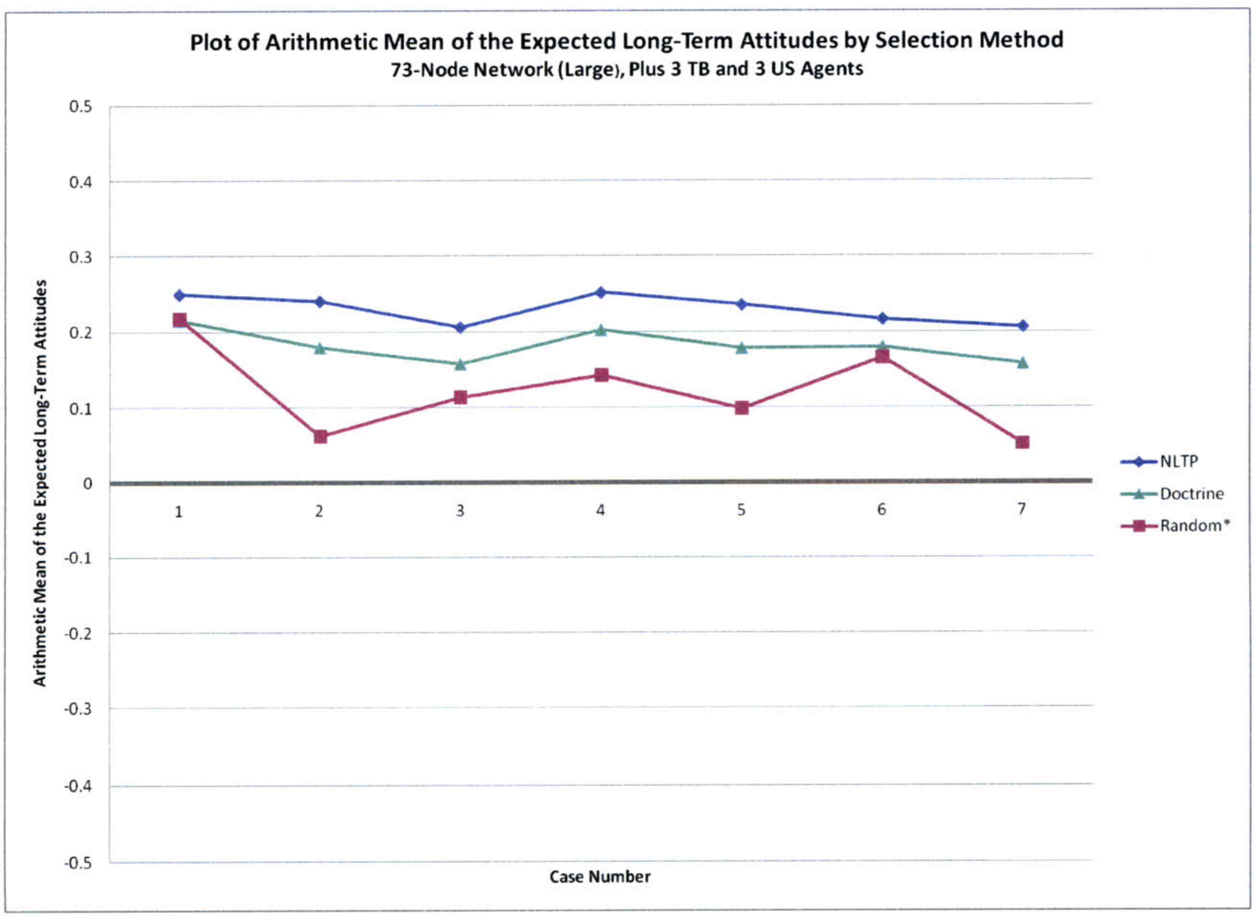

Figure 4-11: Experiment 3B Results-Performance of 3 Selection Methods in 7 Cases

We also produced a visual representation of the analytically obtained expected long-term attitudes of the population achieved by each selection method. These images were appealing in that they showed the expected long-term attitude of each agent in the network as a color code. In this section, we only showed the results from Experiment 3B, case #7. The results for the other cases in Experiment 3B are shown in Appendix B.

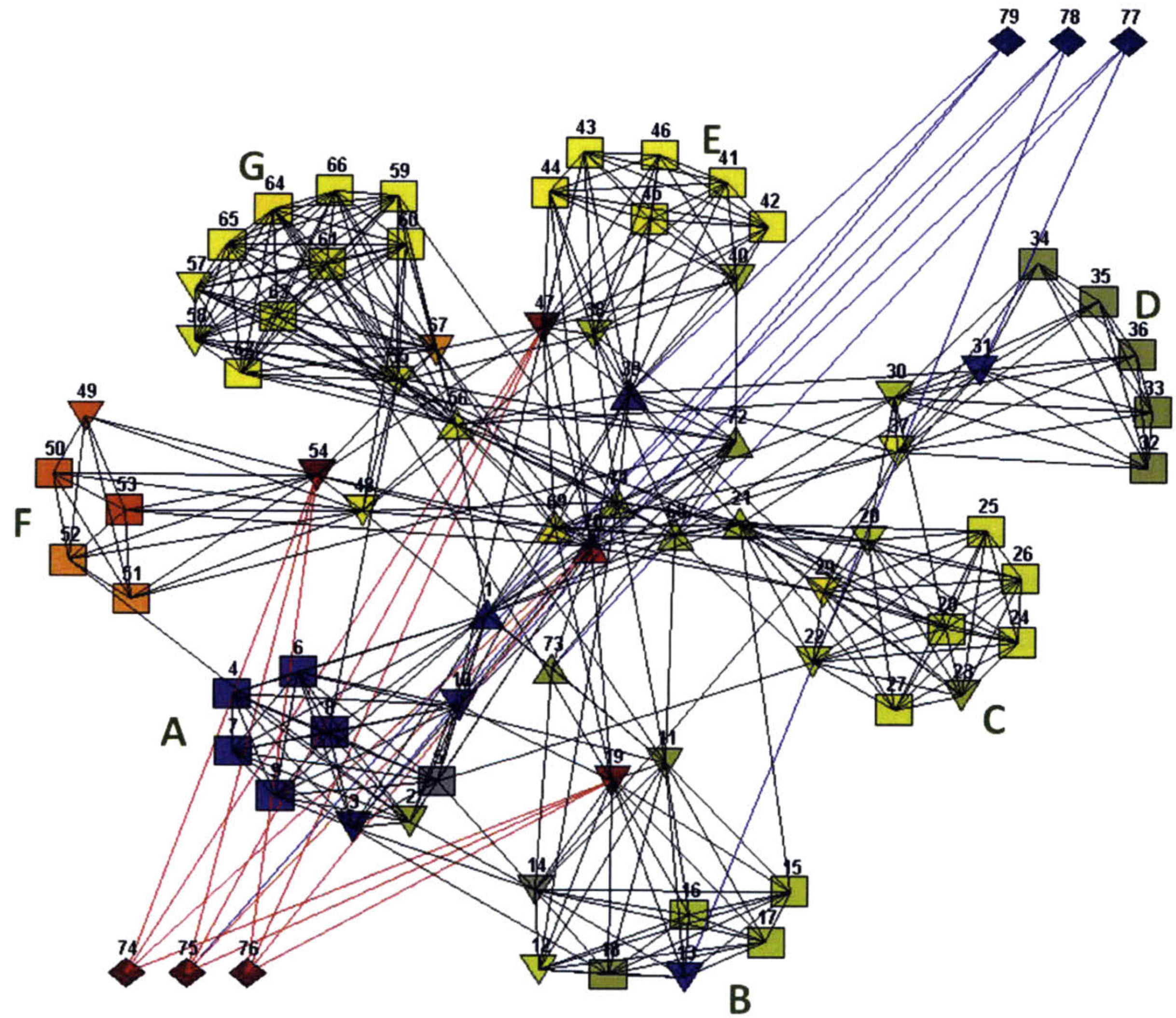

Figure 4-12: Experiment 3B, Case #7- Picture of Expected Long-Term Attitudes for Random Selection

Figure 4-12 depicts the randomly obtained connections for US agents (77, 78, and 79) and the effect on the expected long-term attitudes of the population. We observed that Village F was moderately unfavorable to the US; Villages B, C, E, and G were predominantly neutral; and Villages A and D were slightly in favor of the US.

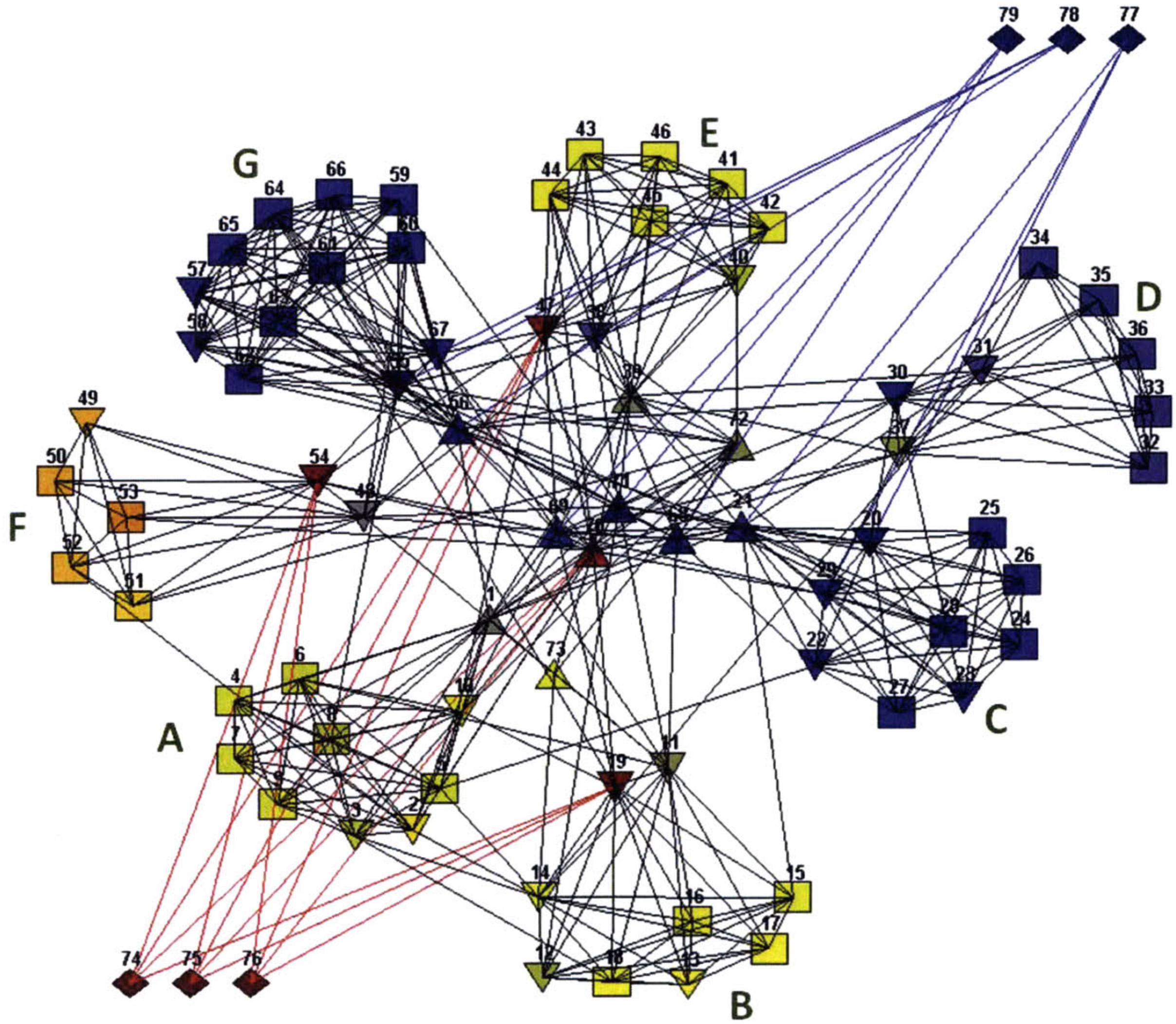

Figure 4-13: Experiment 3B, Case #7- Picture of Expected Long-Term Attitudes for Doctrine-Based Selection

Figure 4-13 depicts the doctrine-based connections for US agents (77, 78, and 79) and the effect on the expected long-term attitudes of the population. We subsequently observed that better sentiments were achieved among the people. Village F was moderately unfavorable to the US; Villages A, B, and E were predominantly neutral; and Villages C, D, and G were moderately to strongly in favor.

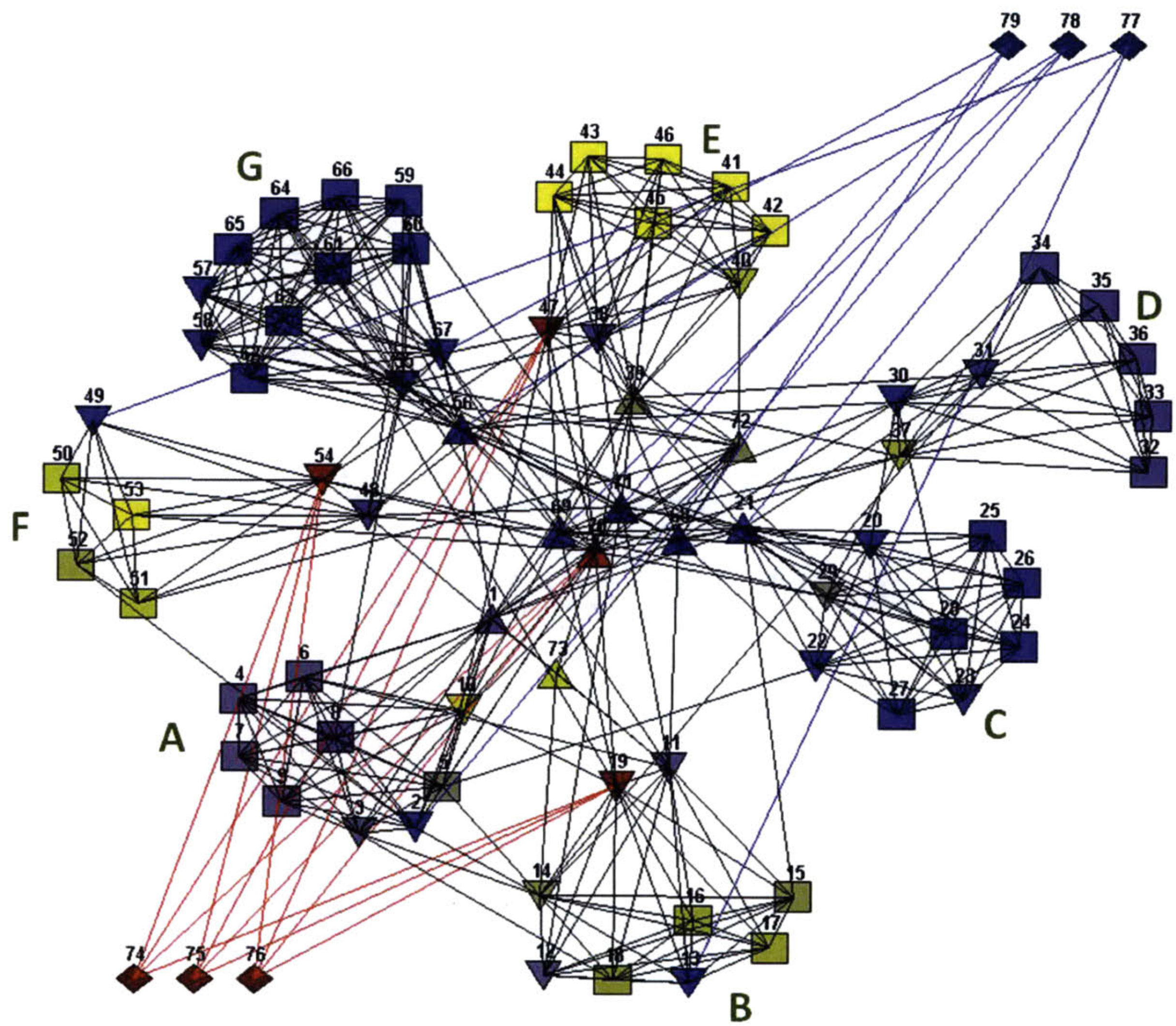

Figure 4-14: Experiment 3B, Case #7- Picture of Expected Long-Term Attitudes for NLTP Optimization-Based Selection

Figure 4-14 depicts the NLTP optimization-based connections for US agents (77, 78, and 79) and the effect on the expected long-term attitudes of the population. We observed an even greater increase in pro-US sentiments achieved among the people. Villages B, E, and F were predominantly neutral; and Villages A, C, D, and G were moderately to strongly in favor.

4.5.2.2 Simulation Performance

In addition to comparing the performance of the methods analytically, we also examined the performance of the selection methods using simulation. For each case, we obtained the targeting assignments based on the various selection methods. We then ran our simulation on each

resulting topology and produced plots of the arithmetic mean of the expected long-term attitude at each interaction, k. We simulated 5000 and 10000 interactions for each network for each case in Experiment 3A and 3B, respectively. Figure 4-15 shows the plots of the arithmetic mean of the expected long-term attitude versus the interaction number k for each of the selection methods in Experiment 3B, case #7. The results for the other cases in Experiment 3B are shown in Appendix B. We conducted 50 realizations for each selection method within each case. Each realization produced an arithmetic mean of the expected long-term attitude (over all agents in the network) for each interaction, k. We then averaged over those realizations to produce the arithmetic mean (over all realizations) of the arithmetic mean (over all agents) of the expected long-term attitudes for each interaction, k. For simplicity, we will refer to these calculations as the *averaged mean expected long-term attitudes*.

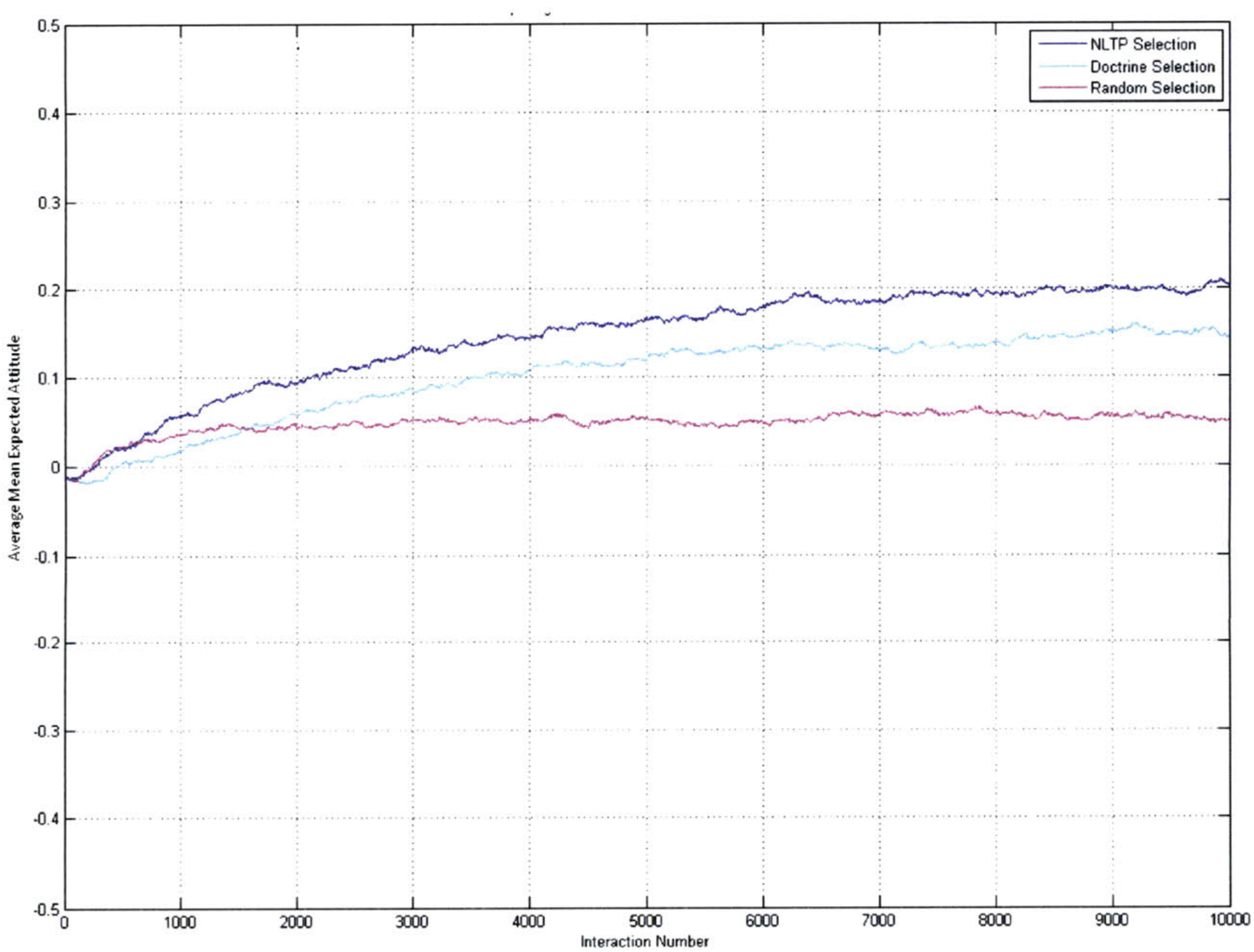

Figure 4-15: Experiment 3B, Case #7 Results-Plot of Averaged Mean Expected Long-Term Attitudes versus Interaction Number

We observed that NLTP optimization-based selection method generally achieved a higher averaged mean expected long-term attitude than the other selection methods. We also observed some interesting results within the first roughly 2000 interactions: 1) up to around the 750th interaction, random selection in fact achieved a slightly higher averaged mean expected long-term attitude than the optimization-based method and 2) up to around the 1600th interaction, random selection achieved a higher averaged mean expected long-term attitude than the doctrine-based method. These observations could be due to stochasticity, or possibly signify that different selection methods may be more appropriate for shorter time horizons as opposed to our optimization-based method used in this work for long-term (infinite) time horizons. This is certainly an area for doing additional analyses or future research.

We also selectively captured the distribution of the mean expected long-term attitudes over all 50 realizations for each selection method at the 5000th interaction to provide additional insight into the simulation results.

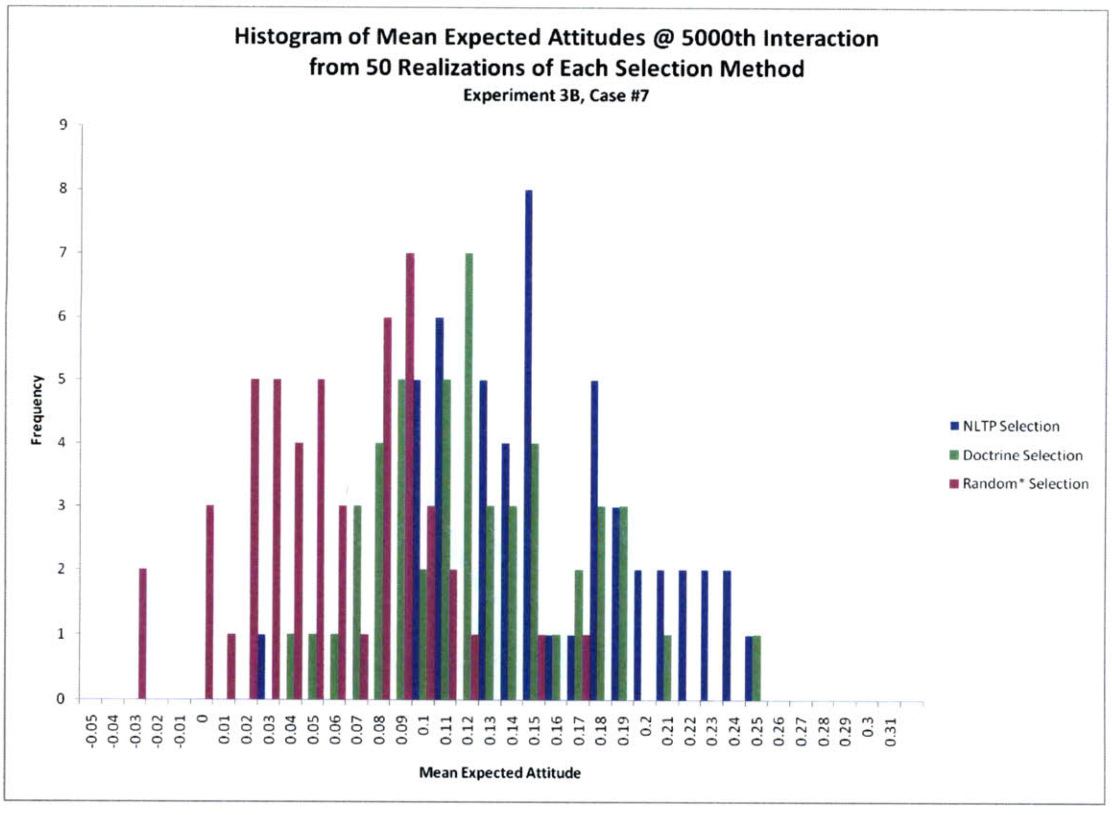

Figure 4-16: Experiment 3B, Case #7--
Histogram of Mean Expected Long-Term Attitudes at the 5000th Interaction Over 50 Realizations of Each Selection Method

Figure 4-16 depicts a histogram approximating distribution of these mean attitudes for each selection method obtained at the 5000th interaction for Experiment 3B, case #7. The plot was produced by sorting the mean expected long-term attitudes into bins of size 0.1. While the distributions were far from separable, we still observed a generally higher performance from the optimization-based selection method.

4.5.2.3 Analysis of the Optimally Selected Agents

In this subsection, we examined the characteristics of the agents that were selected by the optimization-based method in order to detect any possible patterns or insights into the nonlethal targeting assignment problem. In Experiment 3B, using the NLTP1 formulation, there were a total of 38 possible candidates for assignment for each US agent (73 local leaders plus 3 Taliban agents minus 38 regular agents). There were 3 US agents with 3 connections allotted in each case. Aggregated across all 8 cases, there were only 18 different agents selected for assignment to a US agent. Table 4-15 lists these agents, the number of times they were selected across the 8 cases, and their characteristics.

#	Times Selected	Agent #	Village	Village Cluster	Societal Position	Forcefulness Level	Initial Attitude
1	7	21	C	2	District *Jirga* Member/*Khan*	forceful$_1$	0.3
2	7	49	F	3	Village *Jirga*	forceful	-0.2
3	7	69	-	-	District *Ulema*	forceful$_1$	0.3
4	6	56	G	3	District *Jirga* Member	forceful$_1$	0.2
5	6	68	-	-	District Police	forceful$_1$	0.3
6	6	71	-	-	Sub-governor	forceful$_1$	0.3
7	5	1	A	1	District *Jirga* Member	forceful$_1$	0.0
8	4	13	B	1	Village *Jirga*	forceful	-0.3
9	3	12	B	1	Village *Jirga*	forceful	-0.3
10	2	39	E	3	District *Jirga* Member	forceful$_1$	-0.2
11	2	67	G	3	Village *Mullah*	forceful	0.2
12	2	73	-	-	District Criminal	forceful$_1$	-0.4
13	1	2	A	1	Village *Jirga*	forceful	0.0
14	1	19	B	1	Village *Mullah*	forceful	-0.3
15	1	29	C	2	Village *Mullah*	forceful	0.3
16	1	37	D	2	Village *Mullah*	forceful	0.0
17	1	40	E	3	Village *Jirga*	forceful	-0.2
18	1	70	-	-	District *Ulema*	forceful$_1$	-0.3

Table 4-15: Overall NLTP Agent Selection Analysis

At a high level, we observed that some forceful agents are selected more often than some forceful$_l$ agents. We suspected that this is due to the topology and the initial conditions of agent attitudes. For example, agent #49 (forceful Village F *jirga* member) was among those selected most often across the 8 cases. This was likely due to the fact that 1) Village F is small and the *jirga* member has a greater relative influence, 2) Village F was moderately against the US and improving this village's attitude would help the population-wide mean, and 3) other forceful agents in the village were already affected by others since agent #54 (forceful Village F *mullah*) was strongly connected to all Taliban agents and agent #48 (forceful Village F *malik*) was connected to others the US agent favorably influenced (agents #69, 71, 1, and 56). In this way, the optimization-based selection mathematically reasoned through the merits of selecting each agent for targeting.

Further recall that in Experiment 3A cases 2-8, and Experiment 3B cases 2-7 we allowed for non-homogenous US agents based upon resource availability. Given the likelihood of this situation, we also examined the frequency a particular agent was assigned with a high-, moderate-, and low-resourced US agent. We hoped that this will give us insights as to how to prescribe connections for US agents with various forceful influence-type probabilities. Table 4-16 below shows this assignment analysis by US agent type.

We observed that high-resourced US agents were often assigned to the friendly district-level (forceful$_l$) local leaders who have a generally positive effect on attitudes of all village-level leaders connected to them. However, it is also interesting to note that high-resourced US agents were also sometimes even assigned to forceful agents. This was likely due to the same mathematical reasoning explained earlier based on two apparent principles: 1) the need to overcome Taliban influence in certain unfriendly villages, 2) the careful selection of agents to distribute US influence while not being redundant with other US influence efforts.

4.5.3 Experiment 3 Conclusions

In Experiment 3, we demonstrated the potential usefulness of the optimization-based method making nonlethal targeting assignments by showing the performance improvement both analytically and in simulation over doctrine-based and random methods.

	Times Selected									
#	Total	By Hi	By Med	By Low	Agent #	Village	Village Cluster	Societal Position	Force-fulness Level	Initial Attitude
1	6	0	2	4	21	C	2	District *Jirga* Member/*Khan*	forceful$_1$	0.3
2	6	1	2	3	49	F	3	Village *Jirga*	forceful	-0.2
3	6	0	3	3	56	G	3	District *Jirga* Member	forceful$_1$	0.2
4	6	4	1	1	68	-	-	District Police	forceful$_1$	0.3
5	6	4	2	0	69	-	-	District *Ulema*	forceful$_1$	0.3
6	6	4	2	0	71	-	-	Sub-governor	forceful$_1$	0.3
7	5	1	3	1	1	A	1	District *Jirga* Member	forceful$_1$	0
8	4	1	0	3	13	B	1	Village *Jirga*	forceful	-0.3
9	3	1	1	1	12	B	1	Village *Jirga*	forceful	-0.3
10	2	1	0	1	73	-	-	District Criminal	forceful$_1$	-0.4
11	1	0	1	0	2	A	1	Village *Jirga*	forceful	0
12	1	0	1	0	39	E	3	District *Jirga* Member	forceful$_1$	-0.2
13	1	0	0	1	40	E	3	Village *Jirga*	forceful	-0.2
14	1	1	0	0	67	G	3	Village *Mullah*	forceful	0.2
15	0	0	0	0	19	B	1	Village *Mullah*	forceful	-0.3
16	0	0	0	0	29	C	2	Village *Mullah*	forceful	0.3
17	0	0	0	0	37	D	2	Village *Mullah*	forceful	0
18	0	0	0	0	70	-	-	District *Ulema*	forceful$_1$	-0.3

Table 4-16: NLTP Agent Assignment Analysis by US Agent Resource Level (Forcefulness)

4.6 Summary of Experimentation

In this chapter, we conducted various tests of the performance and usefulness of our modeling approach. In Experiment 1, we demonstrated the effect of network size on runtimes and determined the solver settings which produced good local optima reasonably quickly. In Experiment 2, we showed that the optimization model performed fairly well when required to find global optima for specific configurations of small and large networks. Lastly, in Experiment 3, we demonstrated the merits of the optimization model in nonlethal targeting with its significantly better performance over both doctrine-based and random methods of assignment in a large network.

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5 Future Research and Application as a Decision Support Tool

In the first part of this chapter, we discuss aspects of our modeling approach for nonlethal targeting that warrants further exploration and research. In the second part of this chapter, we describe how our work can be possibly integrated as a decision support tool to assist in company- and battalion-level nonlethal targeting.

5.1 Future Work

We believe that this work makes a significant contribution in addressing some of the difficulties with nonlethal targeting in COIN. Our modeling approach provides a useful framework for capturing many of the relevant concepts in the problem including: changeable attitudes of local leaders, an approximation of the social interaction network among the population, and probabilistically representing the effect of agent interactions on attitudes. The synthesis of the Afghan COIN social influence and network generation models allowed us to develop a means to quantitatively measure and visualize the effect of nonlethal targeting by US agents. As our experimental results have shown, our methodology produces assignments that perform quite well both analytically and in simulation. However, despite laying this foundation, we recognize that our models require more refinement. We identify several focus areas that warrant further exploration and research: 1) more realistic agent dynamics, 2) shorter time-horizon effects and analysis, 3) adversarial actions and game-theoretic approaches, and 4) alternative formulations of the NLTP model.

5.1.1 More Realistic Dynamics

Our COIN social influence model accounts for very basic types of interactions, namely those which have an averaging, forceful or identify effect on agents' attitudes. While the use of scalar attitudes and different types of interactions is already an improvement from traditional 0-1 (on/off) attitude modeling, we recognize that the dynamics can be improved further still. Specifically, we see the need for future research in incorporating thresholds and boomerang effects.

5.1.1.1 Threshold-Type Models

In our work, agents change their attitudes towards the counterinsurgents after pair-wise interactions with neighbors in a network. Depending on the interaction-type probabilities, usually every interaction involves some sort of adjustment of attitudes, which is not necessarily the case in reality. In order to make these dynamics more realistic, we propose the view that an agent's attitude towards counterinsurgents may very well be a *complex contagion*, a notion that a willingness to adopt an attitude or participate in a collective behavior "require[s] independent affirmation or reinforcement from multiple sources" especially "when these behaviors are costly, risky, or controversial" [96]. We posit that an agent may require confirmation from several other neighbors before it decides to adjust its attitude towards the counterinsurgents (or insurgents). This idea may have validity among Pashtuns who may require reinforcement from other members of the same *qawm* before he changes his attitude.

There are a couple of ways to potentially implement this modification to the model in simulation. First, we can designate for each agent some threshold k that is the number of confirming interactions (signals) an agent requires before he will adjust his attitude in the direction of the previous signals. We can also implement the following: 1) at each time-step, every agent determines the "prevailing sentiment" of his neighbors; and 2) an agent makes adjustments to its attitude not only as a function of the interaction-type probability but whether the other interacting agent's attitude brings him towards or away from this prevailing sentiment.

Despite the apparent ease in implementing this type of dynamic in simulation, we recognize the significant challenge of collecting data of individual local leader thresholds

5.1.1.2 Boomerang Effect

As described in Section 3.3.3, the boomerang effect occurs when agents take on attitudes which specifically oppose that of certain neighbors [66]. There is some anthropological support for this effect among Pashtuns in Afghanistan. Specifically, one of the tenets of *Pashtunwali*, the customary code of Pashtuns, is agnatic rivalry often among cousins. It would be interesting to study further how this modification to the interaction dynamics effects how US agents can best nonlethally target the population.

5.1.2 Short-term Expected Attitudes

In this work, we are concerned with the expected attitudes of the population as the number of interactions gets large. However, as was shown in our experimental simulation results in Section 4.5.2.2, we observed that in some cases at some smaller number of interactions, random assignment methods outperformed the optimization assignment methods. If we consider that many aspects of the operational environment (including influence parameters, Taliban connections, and local leader connections) can potentially change before a large number of interactions occur, we see a strong need for future research in understanding the agent attitude dynamics over shorter time horizons. We believe that a good starting point is by solving equation (3.6) in Section 3.3.4.1, the discrete dynamical system that shows the change in expected attitudes of all agents from interaction k to k+1.

5.1.3 Adversarial Actions and Game-Theoretic Approaches

We made the significant and unrealistic assumption in this work that Taliban agent connections remained fixed over time. In fact, we are likely to observe Taliban agents repeatedly re-evaluating their strategy and initiating a coercion and intimidation campaign targeting those local leaders who are sympathetic to the counterinsurgents. Accordingly, future work in this area needs to take into consideration changing enemy actions when deciding US agent assignments. This is by no means trivial. One can begin by determining an analytic solution to near-horizon expected attitudes (as discussed above) for a particular set of both US and Taliban connections. Afterwards, it may be possible to formulate an optimization problem for each side, US and Taliban, and to analyze how the connection strategies counter one another after a certain number of interactions. What we described is in essence a simulation of some type of sequential game where each side tries to vie for the attitude of the population. Even beyond this, one can explore how to represent this contest as a two-player game and determine some equilibrium which might be helpful in informing US forces how to best counteract the set of possible Taliban actions.

5.1.4 Alternative Formulations

In our NLTP optimization formulation, our objective was to find the US assignment strategy that achieved the maximum arithmetic mean of the expected long-term attitude of all agents in the

network. However, future research should also explore other formulations that would provide additional insight into solving the nonlethal targeting assignment problem.

5.1.4.1 Threshold Objective Function

We posit that there are cases when a commander does not necessarily want to achieve the highest arithmetic mean of the expected long-term attitude. In fact, the commander may choose to conduct nonlethal targeting to win *strong* support, albeit with a smaller number of people or villages. For example, one may want to find the optimal US assignment strategy that maximizes the number of villagers who exhibit expected long-term attitudes greater than some threshold (say 0.25). In order to address this problem, we propose modifications to the NLTP and NLTP1 formulations. Specifically, we can declare a new objective function (5.1) and add three more sets of constraints (5.2-5.4) to the previous formulations:

$$\max_{u} \sum_{i \in \mathcal{A}} value_i \cdot q_i \tag{5.1}$$

$$\text{s.t.} \; \left(\mu_{Y,i} - b\right) \leq q_i \qquad \forall\, i \in \mathcal{A} \tag{5.2}$$

$$\left(b - \mu_{Y,i}\right) \leq (1 - q_i) \qquad \forall\, i \in \mathcal{A} \tag{5.3}$$

$$q_i = \{0,1\} \qquad \forall\, i \in \mathcal{A} \tag{5.4}$$

$$\vdots$$

Constraint (5.4) declares a new binary variable q_i. Constraints (5.2) and (5.3) are paired constraints that ensure that $q_i = 1$ only when $\mu_{Y,i} \geq b$, meaning that agent *i*'s attitude is greater than some threshold b. The objective function (5.1) then gives a value for every villager whose attitude is over that threshold. The point is to get the most number of villagers who are significantly more aligned with US forces than just slightly pro-Taliban or even neutral. It is important to note however that depending on the parameters, network structure, and number of US agents and connections, it may not always be possible to influence even a single local leader's attitude above some threshold b because b is too high and unrealistic. Even this result is useful because it informs the command of the true number of local leaders that he can win over firmly.

5.1.4.2 Multi-Objective Function

While the previous threshold formulation's objective is to maximize the number of agents with an expected long-term attitude above a certain value, we may also be interested in exploring the option of simultaneously using other US connections to maximally raise everyone else's attitudes. We determined through preliminary trials that the threshold formulation ineffectually assigned US connections that were not enough to bring another agent over the attitude threshold. This multi-objective modification to the original NLTP and NLTP1 formulations might involve the following:

$$\max_{u} \ \lambda \cdot \sum_{i \in \mathcal{A}} value_i \cdot q_i + (1-\lambda) \cdot \sum_{i \in \mathcal{A}} \cdot \, value_i \cdot \mu_{Y,i} \tag{5.5}$$

$$\text{s.t.} \ (\mu_{Y,i} - b) \leq q_i \qquad \forall \, i \in \mathcal{A} \tag{5.2}$$

$$(b - \mu_{Y,i}) \leq (1 - q_i) \qquad \forall \, i \in \mathcal{A} \tag{5.3}$$

$$q_i = \{0,1\} \qquad \forall \, i \in \mathcal{A} \tag{5.4}$$

$$\vdots$$

Equation (5.5) is the multi-objective function, where $\lambda \in [0,1]$ is a weight parameter determined *a priori* to balance between achieving the greatest number of agents with expected long-term attitudes over a threshold and achieving the maximum arithmetic mean of the expected long-term attitude of all agents.

5.1.4.3 Constrained Assignment

In order to delineate clear lines of responsibility and authority, US Army units often divide up their area of operations into geographical sub-areas for subordinate units. An example of this in practice is when a company, responsible for an Afghan district, divides up all the villages within that district for each of three platoons in which to conduct COIN operations (e.g., platoon 1 is responsible for villages A,B, and C; platoon 2 is responsible for villages D, E, and F; and platoon 3 is responsible for villages G and H). However, our model fails to take these assignment constraints into account when determining the optimal targeting strategy and can conceivably assign two different US agents (say two platoons) to connect with different local leaders in the same village. Future work needs to be done to modify the constraints of the NLTP and NLTP1 formulations to account for these realistic exogenous assignment constraints.

5.2 Application as a Decision Support Tool

In this section, we discuss briefly how this modeling approach can be integrated into the US Army's nonlethal targeting process as well as the some insights about data collection.

5.2.1 Integration into Nonlethal Targeting

In Section 2.5.2, we described the functional decomposition of the nonlethal targeting process, a process by which the US Army identifies, prioritizes, and allocates resources to engage nonlethal targets. We believe that the suite of models we developed in this thesis, collectively called the *NLTP decision support tool*, can be integrated into this process to aid commanders and staffs in determining the best courses of action (COA) to win support of the population. This decision support tool is most suited to help in the *Decide* step in targeting process, depicted in Figure 5-1.

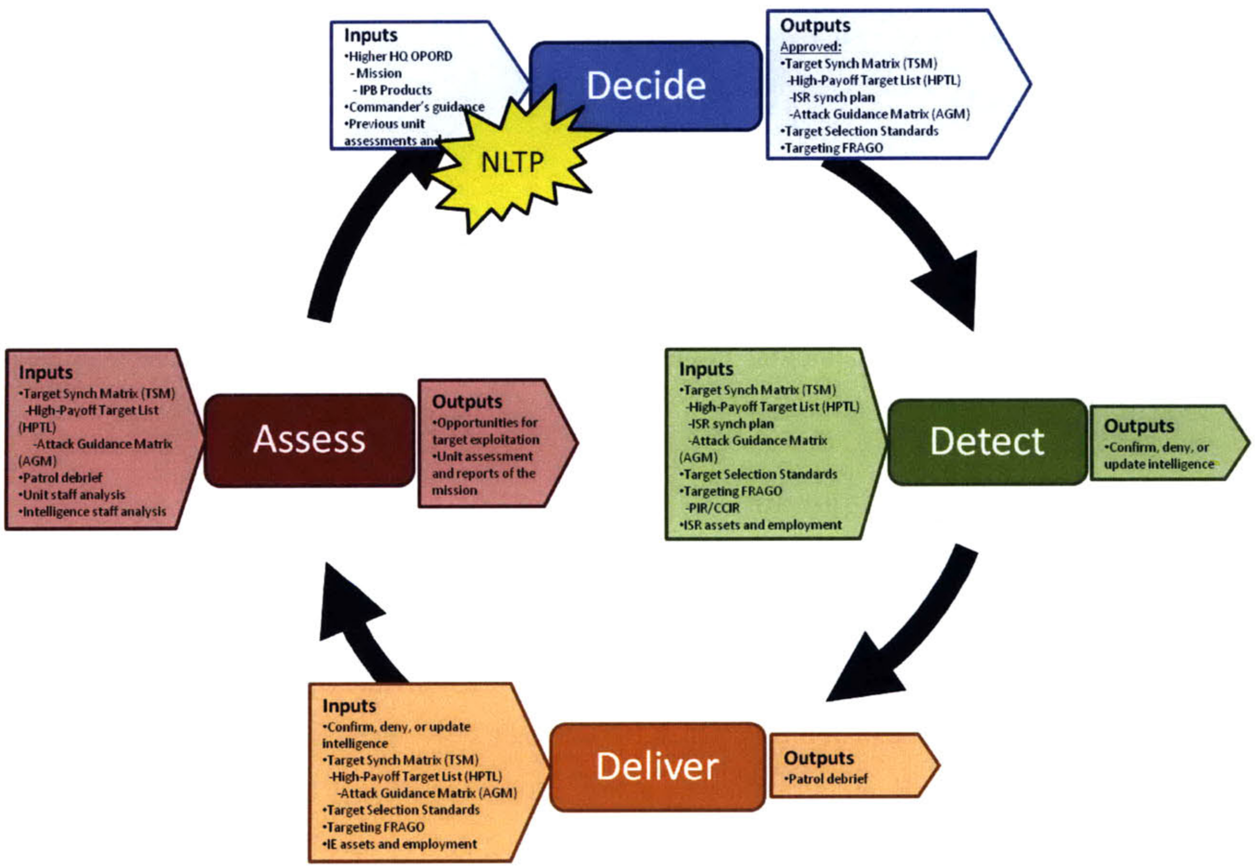

Figure 5-1: NLTP Decision Tool in the Targeting Process

The NLTP Decision Support Tool would receive inputs (such as Intelligence Preparation of the Battlefield (IPB) products and analysis, and the human intelligence gathered from soldiers in

previous operations) that already currently feed into the *Decide* function. The user of the tool, who we recommend to be an intelligence staff officer, would employ the tool to provide to the targeting working group with quantitative analysis of targeting specific individuals and to enable the working group to perform "what-if" analysis. The model and other inputs can be refined through repeated iterations of the targeting process.

Within the *Decide* function, the NLTP decision support tool can aid the commanders and staffs by helping them complete specific tasks. These tasks are highlighted in red and shown in Figure 5-2. We describe how the tool assists in each of these steps below.

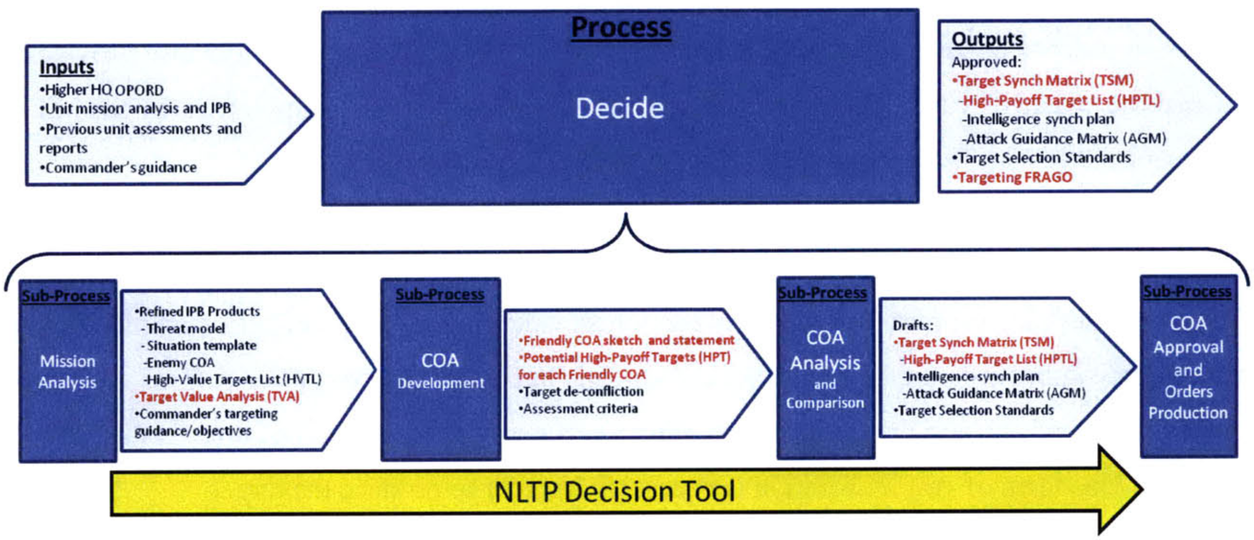

Figure 5-2: NLTP Decision Tool Integration into the Decide Function

5.2.1.1 Target Value Analysis (TVA)

One of the problems that staff officers in the targeting working group currently have is conducting a rigorous target value analysis. This analysis is supposed to detail how an individual enables enemy actions. For example, this analysis might address how a pro-Taliban *mullah* from Village A affects the attitudes of the population and enables the Taliban forces by providing popular or logistical support. The NLTP decision support tool provides staff officers with a means to conduct quantitative analysis and to predict the effect on the sentiments of the population if US forces had co-opted those individuals. This level of analysis and predictive capability help inform the targeting working group of the value of one nonlethal targeting strategy over another.

5.2.1.2 High-Payoff Target List (HPTL)

Staff officers repeatedly assess and pare down the high-value target list (HVTL) (which is a list of local leaders determined by intelligence analysis to be valuable in winning support) to a high-priority target list (HPTL). The HPTL ranks in order of precedence the individuals in the HVTL which should be targeted. The NLTP decision support tool can perform this task quite rapidly and provide qualitative support to prioritizing some local leaders over others.

5.2.1.3 Course of Action (COA)

Once the HPTL is determined, staff officers must also develop synchronized plans, known as COAs, in order to conduct the targeting actions. The NLTP decision support tool also provides an analytic "what-if" capability that allows the user to test the result of assignments by specific US agents.

5.2.1.4 Target Synchronization Matrix (TSM)

The NLTP decision support tool currently cannot provide analysis of the effect on attitudes when targeting assignments are executed at different points in time. However, it can inform commanders and staff on the effect of assigning a certain set of targets to one unit versus another. This form of synchronization is necessary in order to produce the target synchronization matrix.

5.2.1.5 Targeting FRAGO

Lastly, all of the above tasks, aided by the NLTP decision support tool, are also used to create the targeting FRAGO, the order which instructs subordinate units whom to nonlethally engage, with what means, and at what times.

5.2.2 Data Collection

We believe that we have made appropriate use of data from specific case studies by cultural anthropologists and political scientists, polls by various agencies, and case studies from field researchers to arrive at a notional but accurate representation of the rural Pashtun social influence structure. However, collecting true empirical data on the village- or district-level social network and the level of influence of each local leader in Afghanistan is difficult for two reasons. First,

Afghanistan is a third-world country with little of the technological innovations (like the widespread use of cell phones or internet) that have offered recent social scientists opportunities to collect rich data sets on networked human interactions and creative ways to conduct experiments on a subject's influence over known networks[15]. Most research on Afghan attitudes still rely on self-reporting and questionnaires, and there is some cause to believe that any social network data collected in this manner may be debatable in reliability and accuracy [97]. Second, because Afghans live in an environment where they perceive threats from both insurgents and counterinsurgents, we suspect that self-report data on ties and attitudes is not only inaccurate but perhaps protectively untruthful as well ([81], [13]). Given this difficulty, we recommend exercising careful construction and analysis of data collection efforts in this area. Future work on parameter and network sensitivity analysis also needs to be done to find targeting assignments when portions of the data are approximations or simply unknown.

As US soldiers conduct missions in these villages and get to know particular local leaders and their relative influence among other actors, many of the generalizations used in the models can be tightened and produce more tailored targeting assignments to increase public support. Currently, the US Army is employing Human Terrain Teams (HTT) to collect cultural and ethnographic data from among the Afghans to help inform commanders of the population sentiments, needs, and potential issues and persons to leverage to win popular support. They have produced questionnaires that have already been used in the field to collect information relevant to this work. These questionnaires are shown in Figure 5-3 and Figure 5-4.

[15] For more on this line of research, see for example [110], [111], [112].

I am interested in learning about the tribes. I would like to learn about your tribe and which tribes are above and below your tribe.

1. What is your Ethnicity?
a. Pashtun?
b. Tajik?
c. Other?
2. What is your tribe?
3. Which tribes are under your tribe?
4. Which tribes are above your tribe?
5. Would you write the information for me in Pashto?
6. What is the history of your tribe?
a. How long has your tribe been in this area?
b. Are they any disputes with other tribes?
c. Which tribes are your allies?
d. What other villages do people of your tribe live?
7. In which other villages do people in your in your village have family?
8. What it your first language?
9. Why is that your first language?
a. Is that the language of your mother?
b. Is that the language of your Father?
c. Is that the language of your village?

Figure 5-3: Example Tribal Questionnaire [98]

Government Official Semi-Structured Questionnaire

Human Terrain Team, 4th Brigade Combat Team, 82nd Airborne Division
24 February 2008

Research Program: The objective of this research program is to examine the inter-relationship between: official's backgrounds; their affiliations and relationships (their current and previous ties); and their values (views of future action). Critical questions include: Are affiliation networks intermingled or distinct? Do individuals cooperate and communicate with those with different backgrounds? Some tentative hypotheses include:
Historic affiliation determines current political position
DSGs come from more similar rather than dissimilar backgrounds
DSG ties constitute a distinct separate social network, separate from other networks

Visual Assessment: Assess who spends time together; Observe formal seating versus informal interactions.

Prior to beginning interview determine whether official has completed the questionnaire.

Personal Background:
How old are you?
Where were you born?
Where were you raised?
What is your qawm and khel?

Where and when did you finish your school?
What groups have you previously belonged to (NGOs, universities, newspapers, tanzims)?
Are you a meshar or mawlawi?

What is your father's profession?
What are your brothers' professions?
Do you have relatives who work in government, police or military?
If you have family members in the government, how can you help each other for solving problems?
What did you do during previous governments?
Please list any previous government positions (years held, district, province):

Government Background:
What is your position?
How long have you been in this position?
What are the responsibilities of your position?
How did you decide to become a [insert position]?
How were you selected for a government position?
Who first recommended you for a government position?
Can you support your family by doing this job?

Network and Affiliation Mapping:
What 5 people here have you known the longest?
What 5 people here were you most recently in contact?
Who are the most important people here?
Who are the most important people in Logar?
What other provincial officials do you work with?
What DSGs do you know the best? How long have you known them?
We heard that one can only become the DC if he knows some government official. Is that true?
We heard that one of Logar's DC is the most powerful. Can you tell us who he is?

Views on DSGs District Commissioners:
What is the job of a sub-governor?
What qualities should a sub-governor or district commissioner have?
What are DC's responsibilities to the Provincial Governor?
What is the DC's responsibility to the people?
What kind of Government officials do the people want? Do they want religious people, educated people, or Mujahid?
Who should get the higher positions, in your opinion?
Why do people want to get higher positions?
Currently, what kind of people can easily get high government positions?

Views on Afghanistan:
What needs to be done in Afghanistan?
How does the current government compare to previous governments?
What is a good government?
How should government be run?

Produced by Tom Garcia and Michael Bhatia Version 2 Aug 2008

Figure 5-4: Example questionnaire for assessing influence and connections [99]

6 Summary and Conclusions

In this chapter we review the work we presented in previous chapters and offer some conclusions based upon the models, results, and analysis.

6.1 Summary

We identified the nonlethal targeting assignment problem of US forces in the counterinsurgency in Afghanistan. In Chapter 2, we provided a detailed operational overview of the struggle for popular support in counterinsurgencies. We described how US forces view the counterinsurgency operational environment and the most pertinent characteristics of both the population and the insurgents that they must consider in order to be successful. We also provided a functional decomposition of the nonlethal targeting process, a process by which resource-constrained units identify important local leaders to co-opt, and prioritize and synchronize nonlethal engagement efforts in order to win the support of the population. We focused on the *Decide* function in this work and described the difficulties of accomplishing the tasks within it in counterinsurgencies in Afghanistan. Lastly, we illustrated the complexity of conducting nonlethal targeting with a detailed description of the insurgency in Afghanistan and the efforts of the US Army to succeed there.

Having provided an operational overview and where our problem fits within the counterinsurgency context, in Chapter 3 we developed our technical models to address the problem. We formulated three models: the Afghan COIN social influence model, the network generation model, and the nonlethal targeting problem. In the social influence model, we represented the actors in the counterinsurgency in Afghanistan (Pashtun local leaders and US and Taliban forces) as agents in a social network. Each agent possessed a scalar value for its attitude towards the US counterinsurgents, and local leaders changed those attitudes after interactions with network neighbors according to interaction-type probabilities. We derived the method to analytically calculate the expected attitudes of all the agents as the number of interactions approached infinity. In the network generation model, we developed an automated means of approximating the social network among agents by drawing on the concept of homophily as well as allowing the input of specific intelligence-confirmed connections. We also built in functions to account for the possibility of missing connections and ties. Lastly, we formulated the

nonlethal targeting problem as a mixed-integer, nonlinear program (MINLP) designed to find the optimal assignment of US agents to local leaders and Taliban agents which maximized the arithmetic mean expected long-term attitudes of the entire population.

In Chapter 4, we described the conduct of three experiments. The first experiment demonstrated the capabilities of our optimization formulation in finding targeting solutions for 20 US agents and 20 connections each on networks up to 200 agents in reasonable amounts of time. The second experiment demonstrated the performance of the optimization formulation in finding global optima. We tested this by selecting networks of a limited size and comparing the solutions obtained on them by optimization and by a complete enumeration of possible US assignments. We showed that the MINLP found the globally optimal solution in almost all cases. Finally, the third experiment illustrated the value of our work by comparing the simulated and analytic performance of the optimization-based assignment strategy with that of both doctrine-based and control (random) methods of selection. On the large network of 73 nodes, the optimization-based assignment performed significantly better analytically as well as in simulation.

In Chapter 5, we identified areas for future research and proposed how this work can be integrated into the US Army targeting process. The four areas for further research were: 1) more realistic agent dynamics, 2) shorter time-horizon effects and analysis, 3) adversarial actions and game-theoretic approaches, and 4) alternative formulations of the NLTP model. We also proposed where this suite of models, what we called the nonlethal targeting decision support tool, can be integrated into the existing US Army targeting process. We described how this tool can be extremely useful for determining the value of potential targets and for performing "what-if" analysis in the *Decide* step in nonlethal targeting.

6.2 Conclusions

In this section, we close this work by offering some final conclusions and insights concerning the modeling the social networks and influences among Pashtun local leaders, and the merits of optimization-based methods of targeting.

6.2.1 Modeling Social Networks and Influences among Pasthuns

The operating environment in counterinsurgencies is extremely complex because of the multitude of variables and civilian considerations that US Army units must be concerned about in order to win support of the population. However, given this complexity, we also recognize the need to develop meaningful representations of the interconnectedness of the population and suggest the application of social networks to that end. Our study of Pashtun social structure and influences supports the idea of modeling actors within a counterinsurgency (local leaders and Taliban and US agents) as nodes and the interpersonal influences among them as links. While great care needs to be taken to parameterize the model based on real data, we can clearly see the potential predictive power of this tool to help guide decision making in nonlethal targeting.

6.2.2 Merits of Optimization-Based Methods of Targeting

The optimization-based assignments of US forces to local leaders on large networks achieved significantly higher arithmetic mean of the expected long-term attitudes than doctrinal-based strategies. Our approach is a consistent, quantitative method of determining the value of US assignments to specific individuals in a counterinsurgency in Afghanistan. Previously, commanders and staffs relied on intuition, doctrinal training, and the qualitative analysis of intelligence in order to determine the high priority target list (HPTL) and conduct the target value analysis (TVA). Our modeling approach and optimization-based method of target selection, however, provide a systematic means to 1) synthesize intelligence and incorporate human-in-the-loop parameterization of interpersonal influences, 2) generate interaction networks supported by intelligence analysis and social science, and 3) quantitatively determine the potential value of a nonlethal targeting assignment strategy as well as its predicted effect on the population. This technology's capabilities signify that it as an important step to helping commanders and staffs solve the nonlethal targeting assignment problem.

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Appendix A Abbreviation and Acronyms

Abbreviation/ Acronym	Term
AGM	attack guidance matrix
AO	area of operations
ASCOPE	areas, structure, capabilities, organization, people and events
COA	courses of action
COIN	counterinsurgency
FM	field manual
FRAGO	fragmentary order
HPTL	high payoff target list
HQ	headquarters
HTT	Human Terrain Team
HUMINT	human intelligence
HVTL	high value target list
IPB	intelligence preparation of the battlefield
ISAF	International Security Assistance Force
KPP	key person problem
LOE	line of effort
MDMP	military decision making process
METT-TC	Mission, enemy, terrain and weather, troops and support available, time available, and civil considerations
MINLP	mixed-integer, nonlinear problem
NATO	North Atlantic Treaty Organization
NLP	nonlinear program
NLTP	nonlethal targeting problem
NPS	Naval Postgraduate School
OE	operational environment
OPORD	operations order
PMESII-PT	Political, military, economic, social, information, infrastructure, physical environment, and time
PS	Personality Strength
S2	intelligence section of a US army unit (brigade and below)
SWEAT-MSO	Sewage, water, electricity, academics, trash, medical, safety, and other considerations
TB	Taliban
TRAC	Training and Doctrine Command Analysis Center
TSM	target synchronization matrix
TVA	target value analysis
US	United States
WTA	weapon-target assignment

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Appendix B Experimental Data and Results

B-1. Datasets for Large and Small Networks (Excel Format)

	Location		Dimensions of Influence (District and Below)														Other Characteristics		Taliban Agents and Connections		
			Household {regular}	Village {forceful}						District/Village Cluster {forceful_1}											
Agent #	Village	Village Cluster	Head of Household	Khan (subtribe)	Jirga (village)	Village Mullah	Local Commander	Village Malik	Local Criminal	Khan(tribe)	Jirga (district)	Member of Ulema	Regional Commander	Sub-Governor	Police Chief	Regional Criminal	Attitude	Value	TB 1	TB 2	TB 3
1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	-0.3	1	0	1	0
2	1	1	1	1	0	0	0	1	0	0	0	0	0	0	0	0	-0.3	1	1	0	0
3	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
4	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
5	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
6	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
7	2	2	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0.3	1	0	0	0
8	2	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
9	2	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
10	2	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
11	2	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
12	3	3	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0.3	1	0	0	1
13	3	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
14	3	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
15	3	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
16	3	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0

Figure B- 1: Dataset for Small Network

Familial/Tribal
Religious
Warlord
Government
Criminal/Bandit

Figure B- 2: Legend of Colors for Dimensions of Influence

1	2	3	4	5	6	7	8	9	10	12	13	14	15	16	17	18	19	20	21	22	23
			Dimensions of Influence (District and Below)																Taliban Agents and Connections		
	Location		Household {regular}	Village {forceful}						District/Village Cluster {forceful_1}							Other Characteristics				
Agent #	Village	Village Cluster	Head of Household	Khan (subtribe)	Jirga (village)	Village Mullah	Local Commander	Village Malik	Local Criminal	Khan(tribe)	Jirga (district)	Member of Ulema	Regional Commander	Sub-Governor	Police Chief	Regional Criminal	Attitude	Value	TB 1	TB 2	TB 3
1	1	1	1	1	1	0	0	1	0	0	1	0	0	0	0	0	0	1	0	0	0
2	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
3	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
4	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
5	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
6	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
7	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
8	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
9	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
10	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
11	2	1	1	0	1	0	0	1	0	0	0	0	0	0	0	0	-0.3	1	0	0	0
12	2	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	-0.3	1	0	0	0
13	2	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	-0.3	1	0	0	0
14	2	1	1	0	1	0	0	0	1	0	0	0	0	0	0	0	-0.3	1	0	0	0
15	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.3	1	0	0	0
16	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.3	1	0	0	0
17	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.3	1	0	0	0
18	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.3	1	0	0	0
19	2	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	-0.3	1	1	1	1
20	3	2	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0.3	1	0	0	0
21	3	2	1	1	1	0	0	0	0	1	1	0	0	0	0	0	0.3	1	0	0	0
22	3	2	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0.3	1	0	0	0
23	3	2	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0.3	1	0	0	0
24	3	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0.3	1	0	0	0
25	3	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0.3	1	0	0	0
26	3	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0.3	1	0	0	0
27	3	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0.3	1	0	0	0
28	3	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0.3	1	0	0	0
29	3	2	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0.3	1	0	0	0
30	4	2	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0
31	4	2	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
32	4	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
33	4	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
34	4	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
35	4	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
36	4	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
37	4	2	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
38	5	3	1	0	1	0	1	1	0	0	0	0	0	0	0	0	-0.2	1	0	0	0
39	5	3	1	1	1	0	0	0	0	0	1	0	0	0	0	0	-0.2	1	0	0	0
40	5	3	1	0	1	0	0	0	0	0	0	0	0	0	0	0	-0.2	1	0	0	0
41	5	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.2	1	0	0	0
42	5	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.2	1	0	0	0
43	5	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.2	1	0	0	0
44	5	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.2	1	0	0	0
45	5	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.2	1	0	0	0
46	5	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.2	1	0	0	0
47	5	3	0	0	0	1	0	0	0	0	0	0	0	0	0	0	-0.2	1	1	1	1
48	6	3	1	1	1	0	0	1	0	0	0	0	0	0	0	0	-0.2	1	0	0	0
49	6	3	1	0	1	0	0	0	0	0	0	0	0	0	0	0	-0.2	1	0	0	0
50	6	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.2	1	0	0	0
51	6	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.2	1	0	0	0
52	6	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.2	1	0	0	0
53	6	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	-0.2	1	0	0	0
54	6	3	0	0	0	1	0	0	0	0	0	0	0	0	0	0	-0.2	1	1	1	1
55	7	3	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0.2	1	0	0	0
56	7	3	1	1	1	0	0	0	0	1	1	0	0	0	0	0	0.2	1	0	0	0
57	7	3	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0.2	1	0	0	0
58	7	3	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0.2	1	0	0	0
59	7	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	1	0	0	0
60	7	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	1	0	0	0
61	7	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	1	0	0	0
62	7	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	1	0	0	0
63	7	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	1	0	0	0
64	7	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	1	0	0	0
65	7	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	1	0	0	0
66	7	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	1	0	0	0
67	7	3	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0.2	1	0	0	0
68	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0.3	1	0	0	0
69	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0.3	1	0	0	0
70	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	-0.3	1	1	1	1
71	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0.3	1	0	0	0
72	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	-0.4	1	0	0	0
73	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	-0.4	1	0	0	0

Figure B- 3: Dataset for Large Network

B-2. Realistic Data

Measure[16]	District	
	Hisarak	**Sherzad**
Estimated population (2002)[17]	28,462	66,392
Average number of households per village	85	124
Average population per village	1,274	1,136
Average population per household	11	7
Average number of village council members (*jirga*)	9	9
Average number of villages[18]	22	58

Table B- 1: Table of Pashtun District Characteristics

B-3. Large Network Agents

Node #	Village #	Village Cluster #	Societal Position	Forcefulness Level	Initial Attitude
1	A	1	District *Jirga* Member	forceful$_1$	0.0
2	A	1	Village *Jirga*	forceful	0.0
3	A	1	Village *Jirga*	forceful	0.0
4	A	1	HH	regular	0.0
5	A	1	HH	regular	0.0
6	A	1	HH	regular	0.0
7	A	1	HH	regular	0.0
8	A	1	HH	regular	0.0
9	A	1	HH	regular	0.0
10	A	1	Village *Mullah*	forceful	0.0
11	B	1	Village *Malik*	forceful	-0.3
12	B	1	Village *Jirga*	forceful	-0.3
13	B	1	Village *Jirga*	forceful	-0.3
14	B	1	Local Criminal	forceful	-0.3
15	B	1	HH	regular	-0.3
16	B	1	HH	regular	-0.3
17	B	1	HH	regular	-0.3
18	B	1	HH	regular	-0.3
19	B	1	Village *Mullah*	forceful	-0.3
20	C	2	Village *Malik*	forceful	0.3
21	C	2	District *Jirga* Member/*Khan*	forceful$_1$	0.3
22	C	2	Village *Jirga*	forceful	0.3

16 All data, unless otherwise specified, is from the National Solidarity Program (NSP) Impact Evaluation study [92].

17 Based upon 2002 UN estimates ([93], [94]).

18 This figure was simply calculated by dividing the estimated population in the district and the average population per village. It is a very rough measure for the number of villages in each district.

Node #	Village #	Village Cluster #	Societal Position	Forcefulness Level	Initial Attitude
23	C	2	Village *Jirga*	forceful	0.3
24	C	2	HH	regular	0.3
25	C	2	HH	regular	0.3
26	C	2	HH	regular	0.3
27	C	2	HH	regular	0.3
28	C	2	HH	regular	0.3
29	C	2	Village *Mullah*	forceful	0.3
30	D	2	Village *Malik*	forceful	0.0
31	D	2	Village *Jirga*	forceful	0.0
32	D	2	HH	regular	0.0
33	D	2	HH	regular	0.0
34	D	2	HH	regular	0.0
35	D	2	HH	regular	0.0
36	D	2	HH	regular	0.0
37	D	2	Village *Mullah*	forceful	0.0
38	E	3	Village *Malik*	forceful	-0.2
39	E	3	District *Jirga* Member	forceful[1]	-0.2
40	E	3	Village *Jirga*	forceful	-0.2
41	E	3	HH	regular	-0.2
42	E	3	HH	regular	-0.2
43	E	3	HH	regular	-0.2
44	E	3	HH	regular	-0.2
45	E	3	HH	regular	-0.2
46	E	3	HH	regular	-0.2
47	E	3	Village *Mullah*	forceful	-0.2
48	F	3	Village *Malik*	forceful	-0.2
49	F	3	Village *Jirga*	forceful	-0.2
50	F	3	HH	regular	-0.2
51	F	3	HH	regular	-0.2
52	F	3	HH	regular	-0.2
53	F	3	HH	regular	-0.2
54	F	3	Village *Mullah*	forceful	-0.2
55	G	3	Village *Malik*	forceful	0.2
56	G	3	District *Jirga* Member	forceful[1]	0.2
57	G	3	Village *Jirga*	forceful	0.2
58	G	3	Village *Jirga*	forceful	0.2
59	G	3	HH	regular	0.2
60	G	3	HH	regular	0.2
61	G	3	HH	regular	0.2

Node #	Village #	Village Cluster #	Societal Position	Forcefulness Level	Initial Attitude
62	G	3	HH	regular	0.2
63	G	3	HH	regular	0.2
64	G	3	HH	regular	0.2
65	G	3	HH	regular	0.2
66	G	3	HH	regular	0.2
67	G	3	Village *Mullah*	forceful	0.2
68	-	-	District Police	forceful$_1$	0.3
69	-	-	District *Ulema*	forceful$_1$	0.3
70	-	-	District *Ulema*	forceful$_1$	-0.3
71	-	-	Sub-governor	forceful$_1$	0.3
72	-	-	Regional Warlord	forceful$_1$	-0.4
73	-	-	District Criminal	forceful$_1$	-0.4

Table B- 2: Condensed List of Agents for Large Network

Note: HH stands for 'head of household.'

B-4. Large Network S2-Directed Connections

Undirected Links		Link Description
14	5	Local criminal to neighboring head of househould
14	3	Local criminal to neighboring village *jirga* member
14	2	Local criminal to neighboring village *jirga* member
73	72	District criminal to district warlord
73	70	District criminal to member of *ulema* (unfavorable to US)
73	48	District criminal to *malik* (unfavorable to US)
73	11	District criminal to *malik* (unfavorable to US)
72	71	Regional warlord to subgovernor
72	70	Regional warlord to *ulema* (unfavorable to US)
72	39	Regional warlord to district *jirga* member from local warlord's village (unfavorable to US)
72	40	Regional warlord to local *jirga* member from local warlord's village (unfavorable to US)
68	21	Police chief to district *jirga* member (favorable to US)
68	22	Police chief to village *jirga* member (favorable to US)
68	69	Police chief to *ulema* (favorable to US)
68	56	Police chief to district *jirga* member (favorable to US)

Table B- 3: List of S2 Connections for Large Network

B-5. Experiment 1 Data Sets

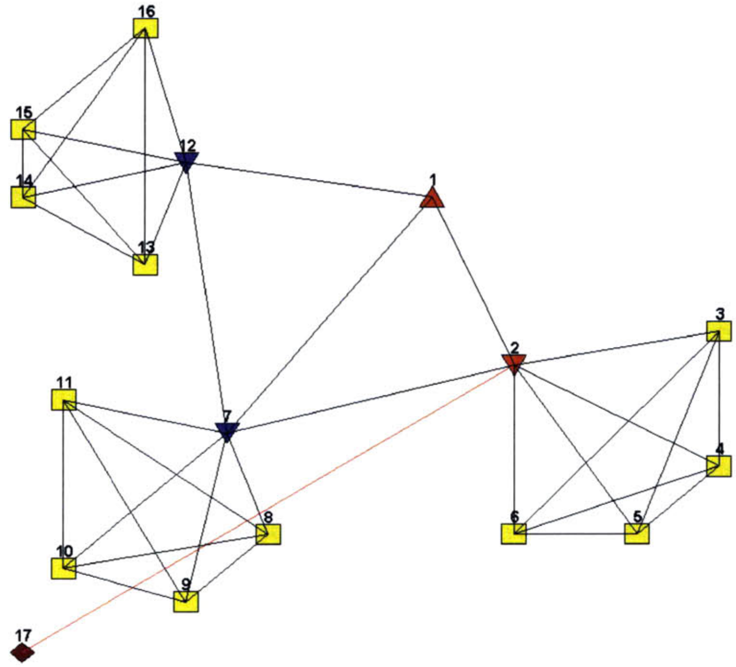

Figure B- 4: Small Network (with 1 Taliban Agent)

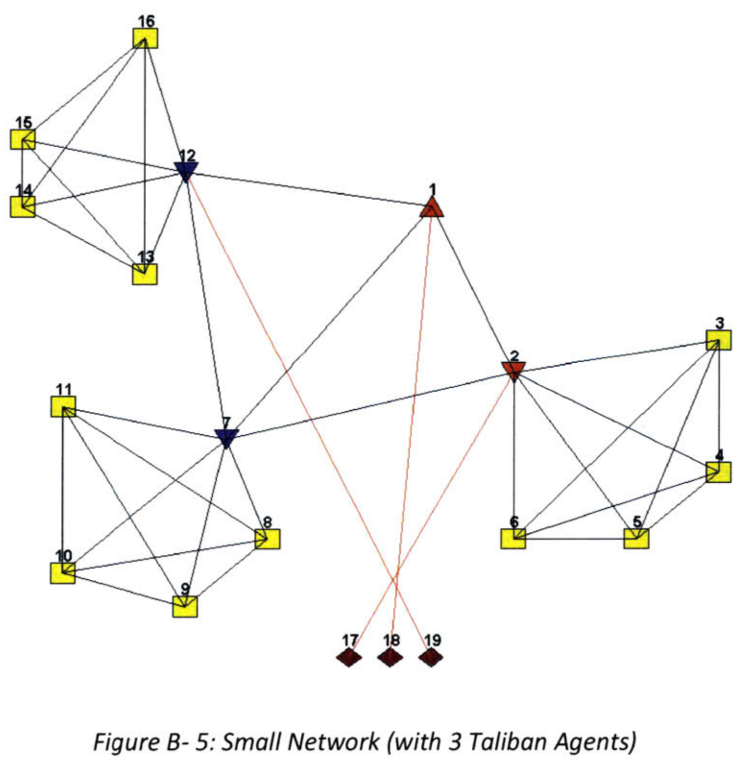

Figure B- 5: Small Network (with 3 Taliban Agents)

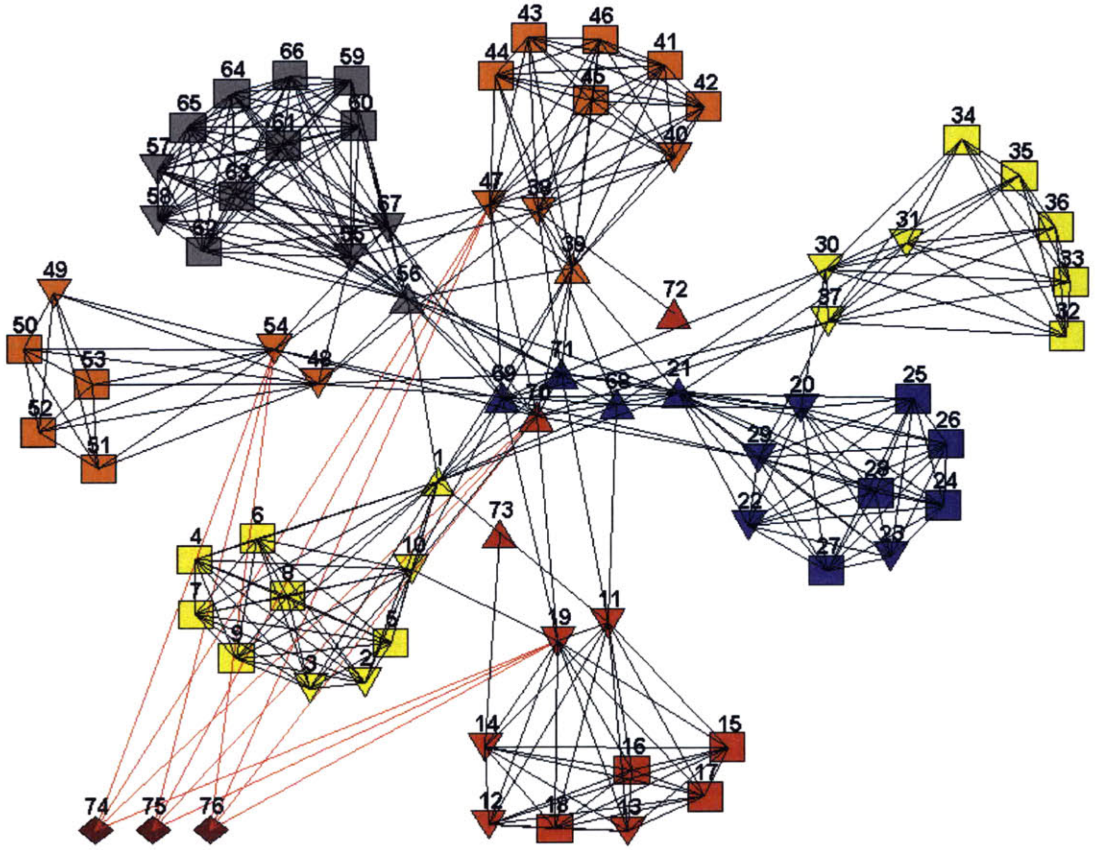

Figure B- 6: Large Network (with 3 Taliban Agents)

B-6. Experiment 1 Results

						NLTP				
Case #	Number of local leaders	Number of Regulars	Number of TB agents	Number of US agents	Connect-ions per US agent	Nodes Visited	Runtime (in secs.)	ms/#	OBJ	Decision
1	16	12	1	1	1	3	10.289	Y/d	0.201785	[17]
2	16	12	1	1	3	3	10.212	Y/d	0.322812	[1,2,17]
3	16	12	1	3	1	23	138.705	Y/d	0.391058	[1],[2],[2]
4	16	12	1	3	3	2	15.922	Y/d	0.451317	[2,3,17],[2,5,17],[1,2,17]
5	16	12	1	3	5	2	13.788	Y/d	0.459645	[2,4,6,1,17],[2,3,5,6,17],[1,2,3,4,17]
6	16	12	1	5	1	11	142.063	Y/d	0.449465	[2][2][1][17][2]
7	16	12	1	5	3	11	123.822	Y/d	0.481257	[2,5,17][1,2,17][2,7,17],[2,4,17][2,3,6]
8	16	12	1	5	5	2	20.812	Y/d	0.483055	[2,3,4,5,17],[2,3,6,12,17],[1,2,6,7,17],[2,3,4,5,17],[2,4,5,6,17]
9	16	12	3	3	1	2	17.798	Y/d	0.0651728	[12][2][7]
10	16	12	3	3	3	15	94.601	Y/d	0.16648	[2,12,17],[1,7,12],[1,2,17]
11	16	12	3	3	5	29	164.162	Y/d	0.235759	[1,2,7,12,17],[1,2,12,17,19],[1,2,12,18,19]
12	16	12	3	5	5	23	201.781	Y/d	0.360519	[1,2,7,12,17],[1,2,12,18,19],[1,3,12,17,18],[2,5,7,12,16],[1,2,12,17,19]
13	73	38	3	1	1	17	1210.499	Y/d	-0.0658268	[71]
14	73	38	3	2	1	181	15246.17	Y/d	0.0965545	[70][71]
15	73	38	3	3	1	-	>50400	Y/d	-	-

Table B- 4: Experiment 1A Results

						NLTP1						
Case #	Number of local leaders	Number of Regulars	Number of TB agents	Number of US agents	Connectio ns per US agent	Nodes Visited	Runtime (in secs.)	ms/#	ms=0 Error from NLTP1hb	% RunTime Savings	OBJ	Decision
6-B2						7	0.064	N/0%	0.00000%	0.04505%	0.449465	[2][2][1][17][2]
13-B2	73	38	3	1	1	15	176.767	Y/100	0.00002%	14.60282%	-0.0658297	[71]
13-B2	73	38	3	1	1	15	16.481	Y/10	0.00035%	1.36150%	-0.065833	[71]
13-B2	73	38	3	1	1	13	0.671	N/	-0.00046%	0.05543%	-0.0658341	[71]
14-B2	73	38	3	2	1	161	2649.34	Y/100	-0.00014%	17.37709%	0.0965562	[70],[71]
14-B2	73	38	3	2	1	123	199.238	Y/10	0.00009%	1.30681%	0.0965539	[70],[71]
14-B2	73	38	3	2	1	31	2.394	N/	-0.22088%	0.01570%	0.094346	[69],[71]
15-B2	73	38	3	2	2	37	4.514	N/	-0.00090%	N/A	0.21885	[1,70],[69,71]
16-B2	73	38	3	3	1	229	35.979	N/	-0.00040%	N/A	0.210042	[69],[70],[71]
17-B2	73	38	3	3	3	159	19.985	N/	-0.40000%	N/A	0.327607	[1,21,39],[49,56,69],[12,70,71]

Table B- 5: Experiment 1B Results

						NLTP1		
Case #	Number of local leaders	Number of Regulars	Number of TB agents	Number of US agents	Connect-ions per US agent	Nodes Visited	Runtime (in secs.)	OBJ
18	100	50	10	5	5	13	8.384	0.343464
19	100	50	10	5	10	35	19.78	0.359555
20	100	50	10	7	5	15	10.797	0.36202
21	100	50	10	7	10	8	5.852	0.371405
22	100	50	10	9	5	11	8.696	0.376617
23	100	50	10	9	10	1333	821.586	0.389183
24	100	50	10	10	10	4846	3175.334	0.395857
25	200	100	20	5	5	57	53.249	0.378942
26	200	100	20	5	10	36	45.640	0.40753
27	200	100	20	10	10	39	85.673	0.436216
28	200	100	20	20	20	8	36.793	0.456267

Table B- 6: Experiment 1C Results

B-7. Experiment 3 Data Sets

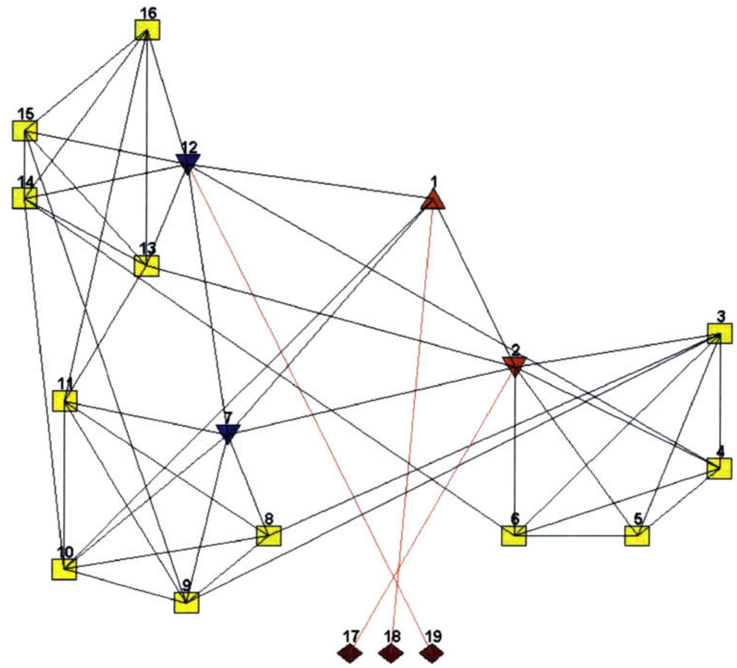

Figure B- 7: Small Network with Uniform Attachment $(\pi = 0.5)$

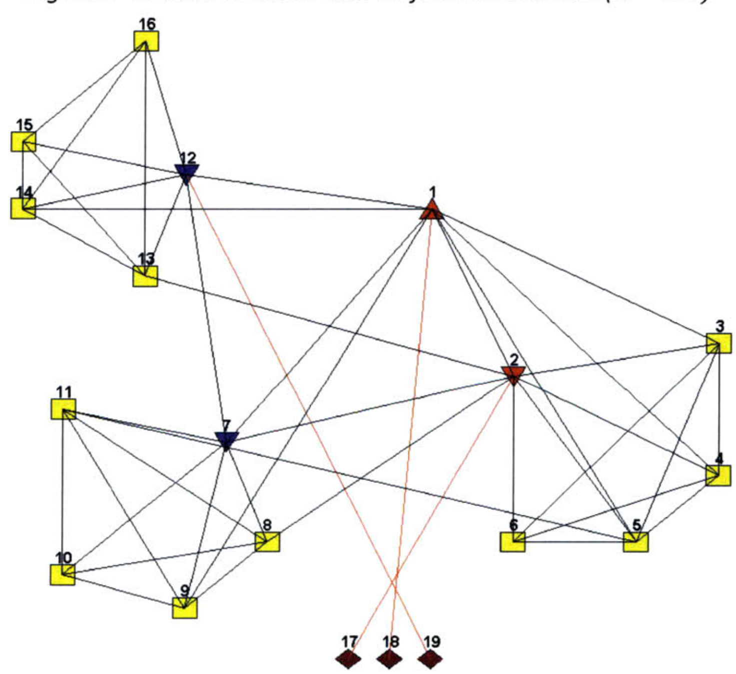

Figure B- 8: Small Network with Preferential Attachment $(\pi = 0.5)$

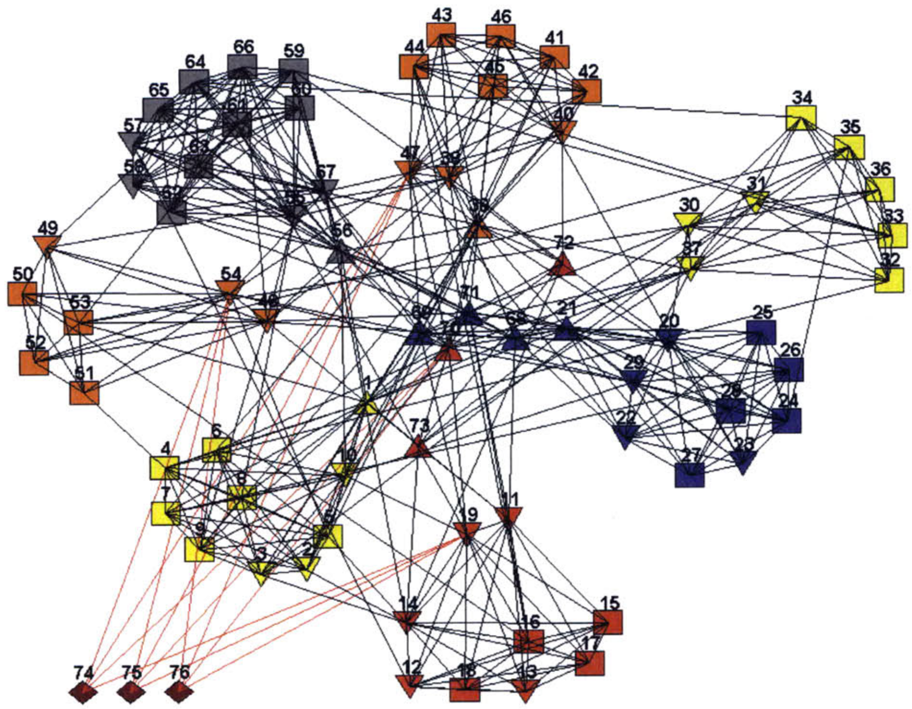

Figure B- 9: Large Network with Uniform Attachment ($\pi = 0.5$)

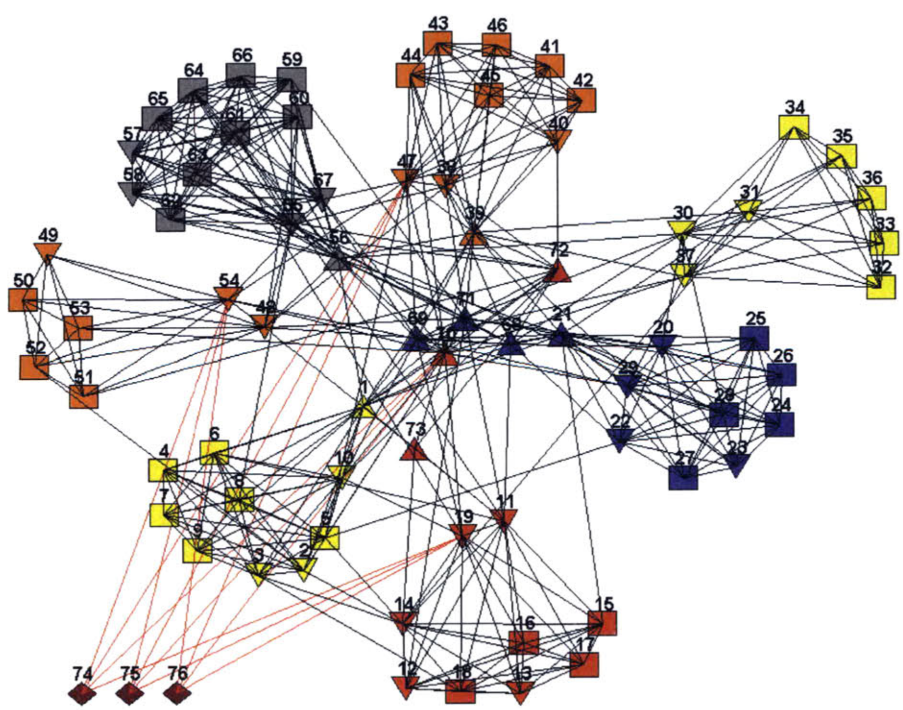

Figure B- 10: Large Network with Preferential Attachment ($\pi = 0.5$)

B-8. Experiment 3 Results

	NLTP1hb.mod					Control (Naïve)			Doctrine-Informed		
Case #	Nodes Visited	Runtime (in secs.)	ms/#	OBJ	Decision	OBJ	Decision	Performance Delta	OBJ	Decision	Performance Delta
1	2	3.913	Y/d	0.0651728	[2][7][12]	-0.2890313	[4][9][3]	-0.3542041	-8.86E-05	[7][12][1]	-0.0652614
2	3	6.267	Y/d	-0.0854988	[2][7][12]	-0.3335	[1][17][12]	-0.2480012	-0.1394	[7][12][1]	-0.0539012
3	3	5.612	Y/d	-0.0268916	[7][2][12]	-0.3896	[6][16][19]	-0.3627084	-0.101	[7][12][1]	-0.0741084
4	3	6.915	Y/d	-0.114279	[7][2][12]	-0.304	[5][2][11]	-0.1897210	-0.1617	[7][12][1]	-0.0474210
5	3	6.94	Y/d	-0.149119	[7][12][2]	-0.4048	[18][12][8]	-0.2556810	-0.1764	[7][12][1]	-0.0272810
6	3	6.202	Y/d	-0.0615016	[7][2][12]	-0.3725	[18][12][18]	-0.3109984	-0.131	[7][12][1]	-0.0694984
7	3	6.193	Y/d	-0.111434	[7][12][2]	-0.378	[4][1][4]	-0.2665660	-0.1533	[7][12][1]	-0.0418660
8	23	33.447	Y/d	3.21E-08	[2][12][1]	-0.2473	[10][6][2]	-0.2473000	-0.0237	[7][12][1]	-0.0237000

Table B- 7: Full Results of Experiment 3A

	NLTP1hb.mod					Control (Naïve)			Doctrine-Informed		
Case #	Nodes Visited	Runtime (in secs.)	ms/#	OBJ	Decision	OBJ	Decision	Performance Delta	OBJ	Decision	Performance Delta
1	24	2.652	N/	0.249689	[37,49,67][21,29,39][19,69,70]	0.2176	[72,68,69][29,74,20][14,37,21]	-0.0320890	0.2151	[21,29,20][67,55,56][69,71,68]	-0.0345890
2	3	0.326	N/	0.24077	[21,56,68][1,12,49][69,71,73]	0.0621	[70,74,29][71,20,3][14,3,1]	-0.1786700	0.1794	[21,29,20][67,55,56][69,71,68]	-0.0613700
3	3	0.276	N/	0.20613	[12,13,56][21,68,71][1,49,69]	0.113	[47,13,56][39,1,21][11,75,1]	-0.0931300	0.1577	[21,29,20][67,55,56][69,71,68]	-0.0484300
4	3	0.398	N/	0.251735	[21,49,56][1,39,71][12,68,69]	0.1424	[39,69,21][56,30,75][23,37,23]	-0.1093350	0.2021	[21,29,20][67,55,56][69,71,68]	-0.0496350
5	2	0.231	N/	0.235697	[13,49,73][1,21,56][68,69,71]	0.0979	[71,73,19][3,21,23][47,72,11]	-0.1377970	0.1782	[21,29,20][67,55,56][69,71,68]	-0.0574970
6	3	0.455	N/	0.216696	[1,21,40][49,56,69][13,68,71]	0.1651	[21,72,40][71,72,21][1,69,11]	-0.0515960	0.1794	[21,29,20][67,55,56][69,71,68]	-0.0372960
7	2	0.294	N/	0.206225	[13,21,49][2,56,69][67,68,71]	0.0514	[31,73,70][1,10,13][75,39,3]	-0.1548250	0.1575	[21,29,20][67,55,56][69,71,68]	-0.0487250

Table B- 8: Full Results of Experiment 3B

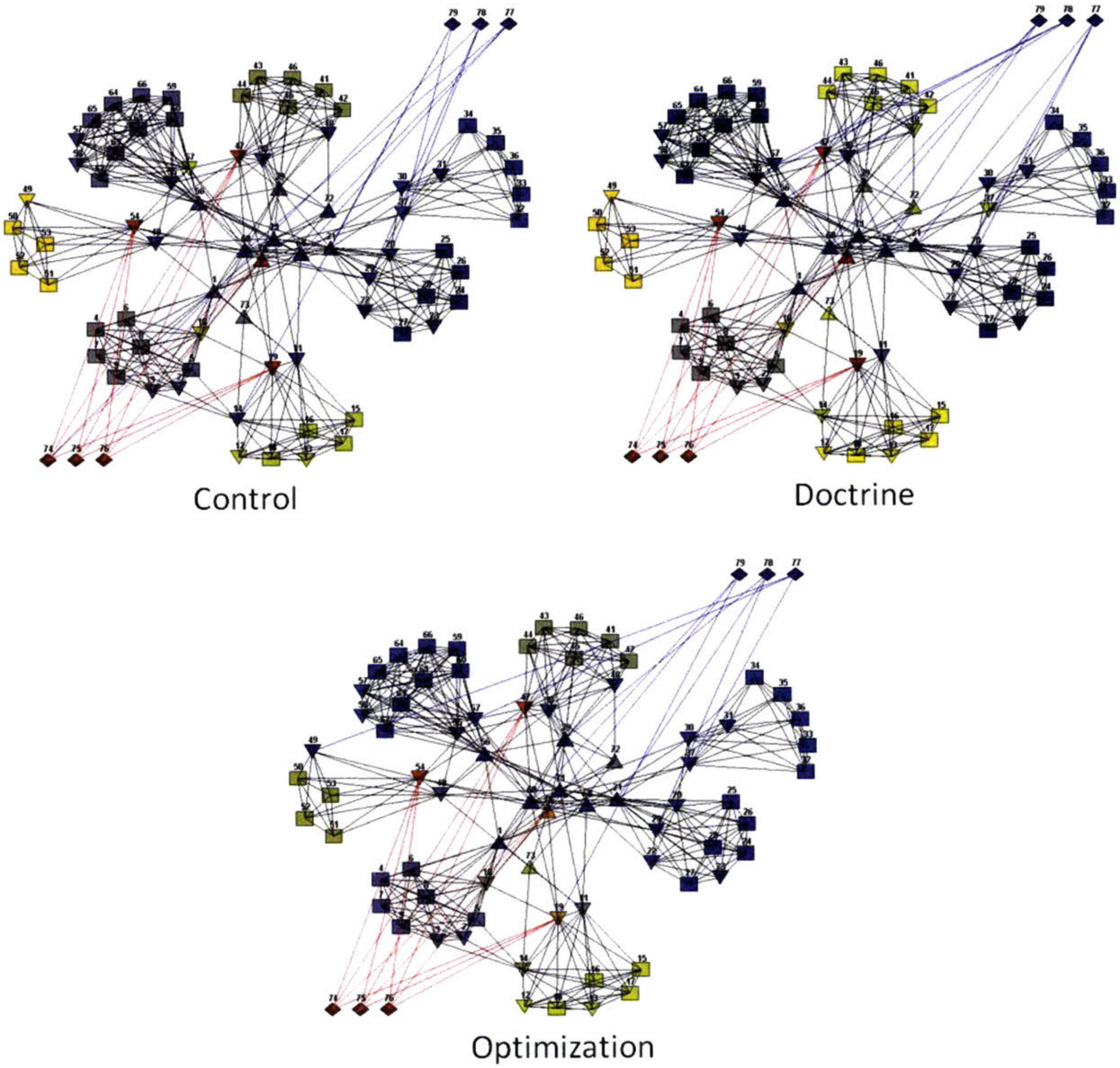

Figure B- 11: Visual Comparison of Expected Long-Term Attitudes by Selection Method of Nonlethal Targets, Case #1

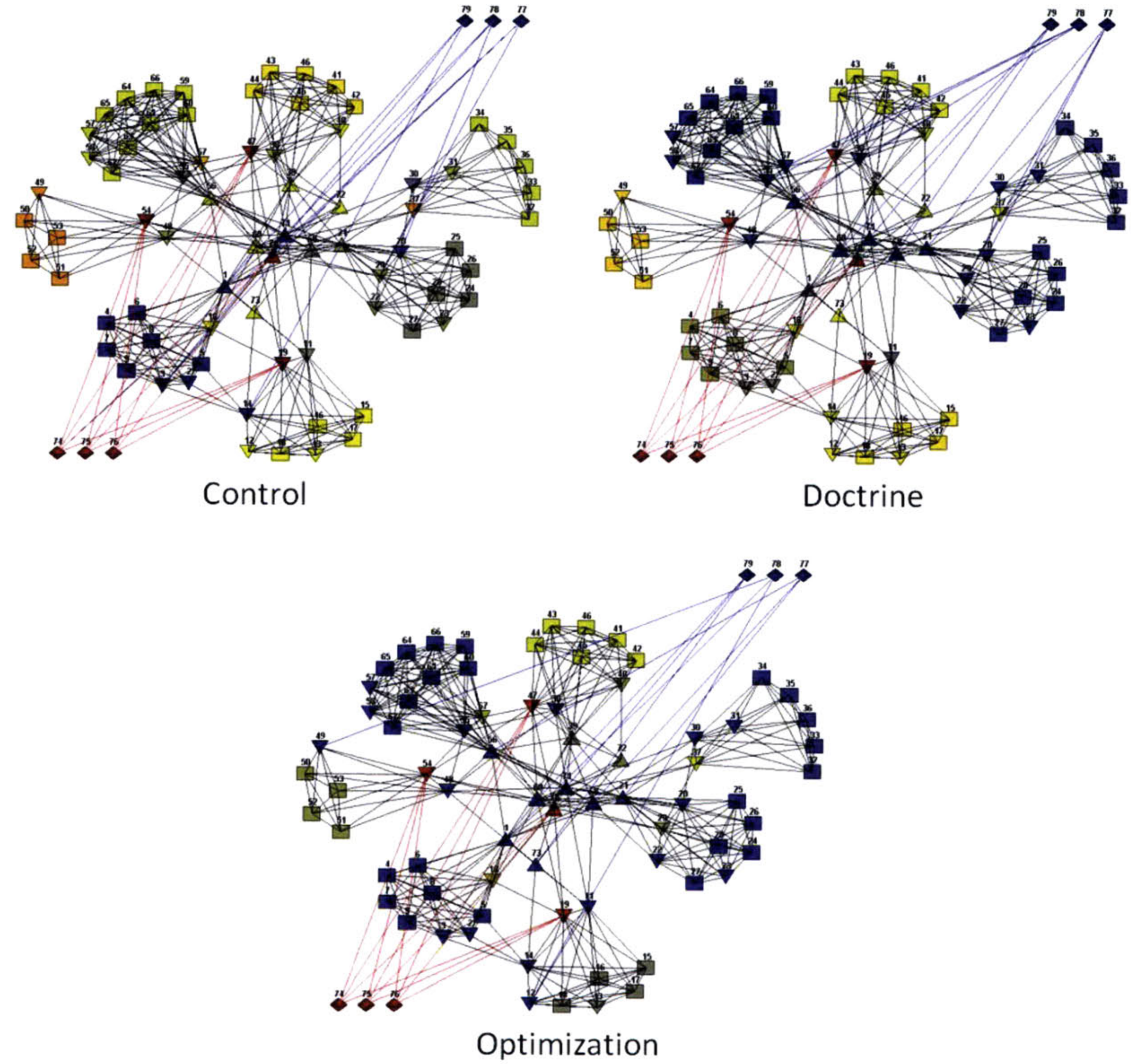

Figure B- 12: Visual Comparison of Expected Long-Term Attitudes by Selection Method of Nonlethal Targets, Case #2

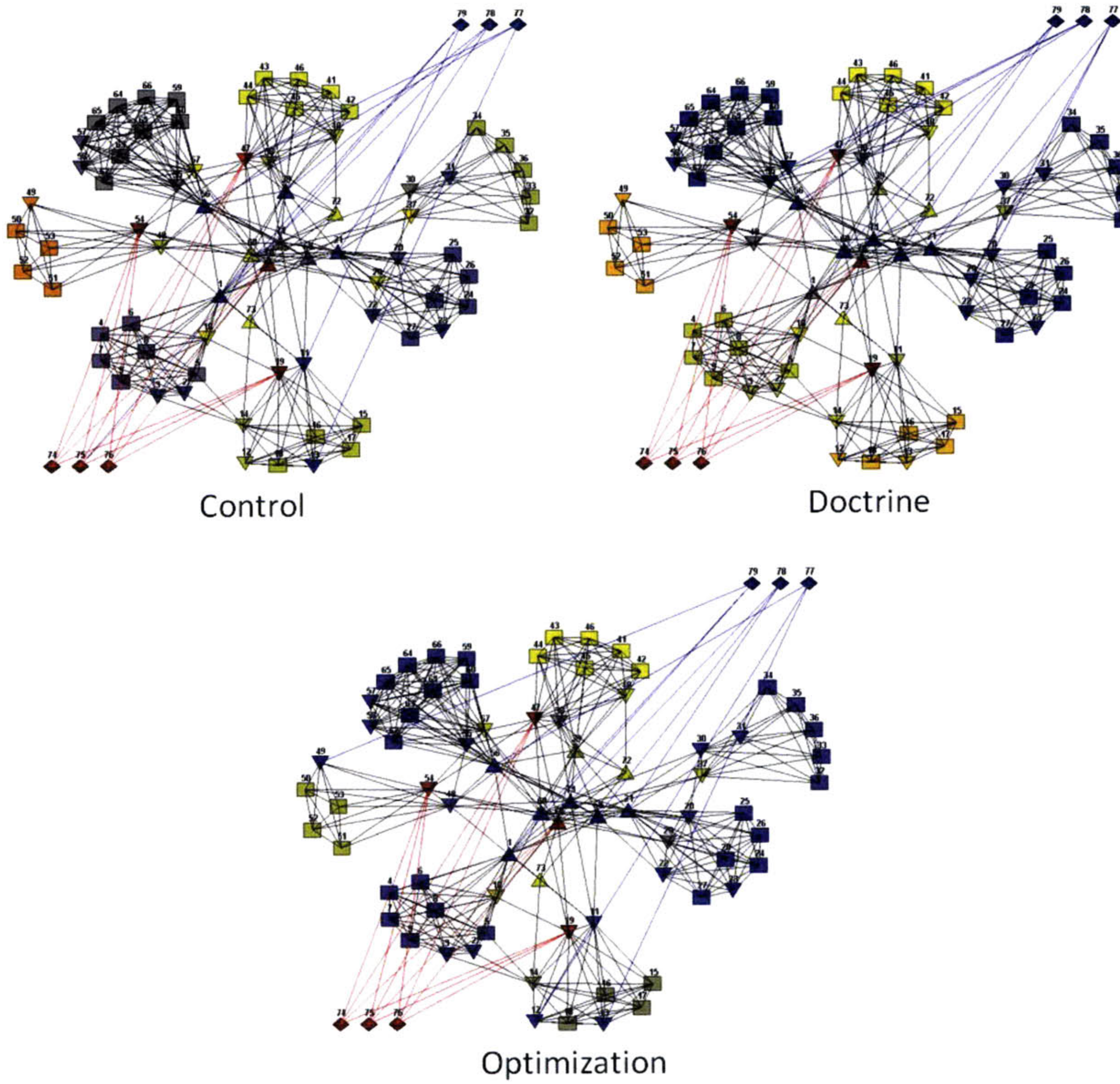

Figure B- 13: Visual Comparison of Expected Long-Term Attitudes by Selection Method of Nonlethal Targets, Case #3

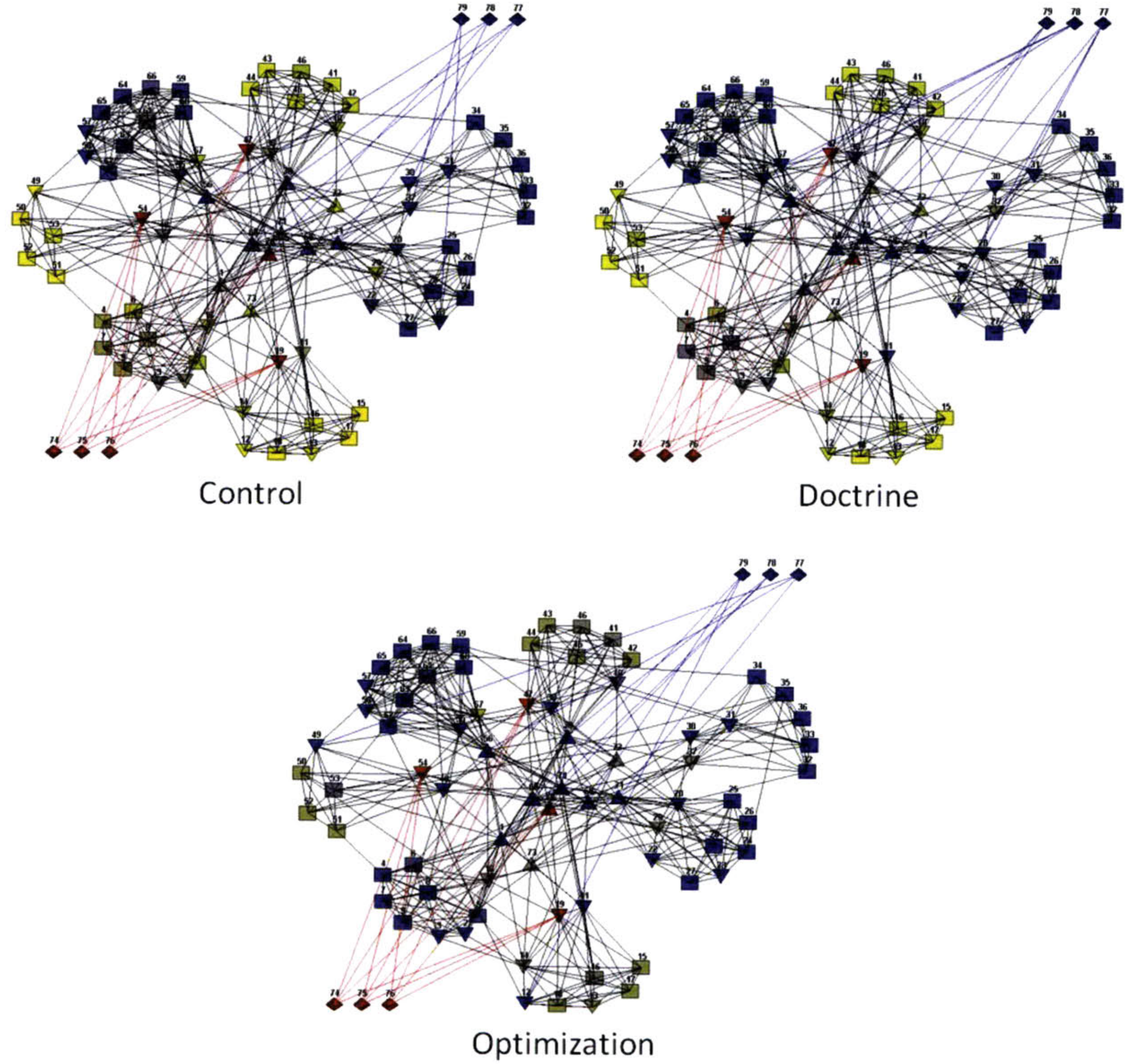

Figure B- 14: Visual Comparison of Expected Long-Term Attitudes by Selection Method of Nonlethal Targets, Case #4

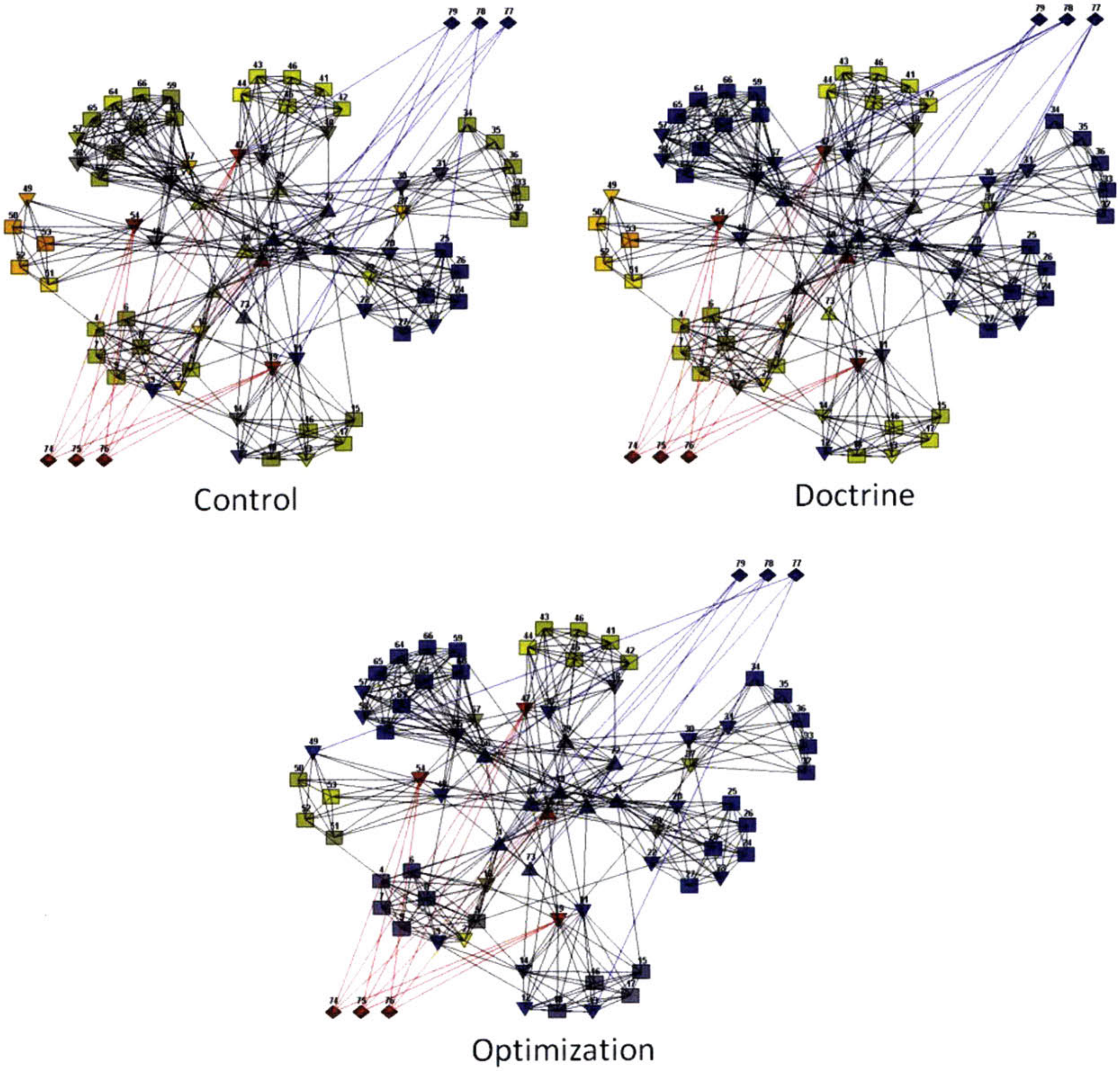

Figure B- 15: Visual Comparison of Expected Long-Term Attitudes by Selection Method of Nonlethal Targets, Case #5

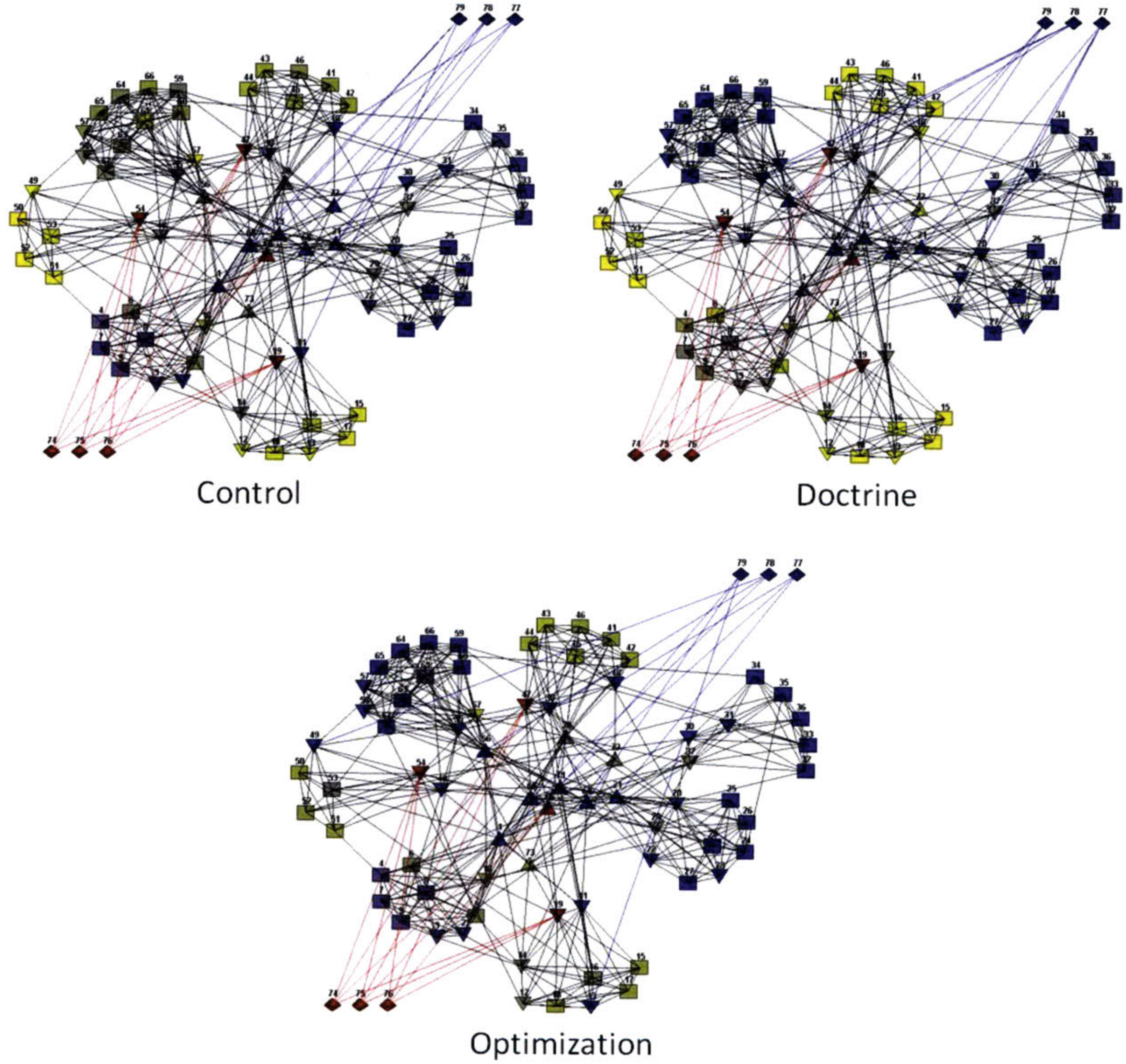

Figure B- 16: Visual Comparison of Expected Long-Term Attitudes by Selection Method of Nonlethal Targets, Case #6

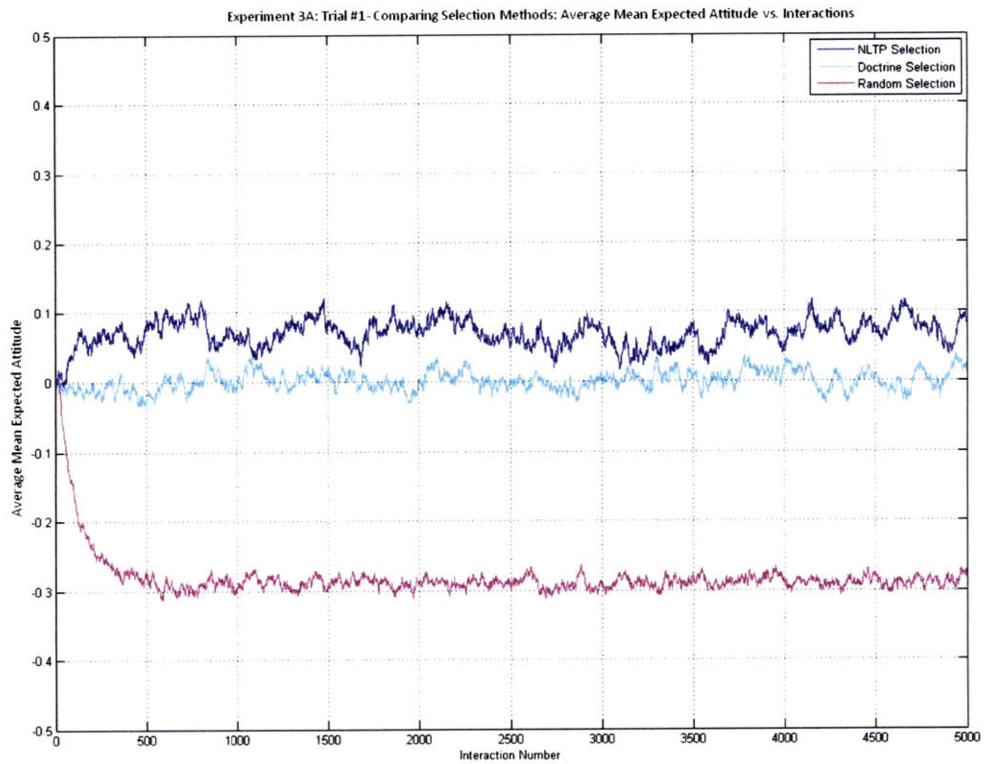

Figure B- 17: Simulation Performance, Experiment 3A, Case #1

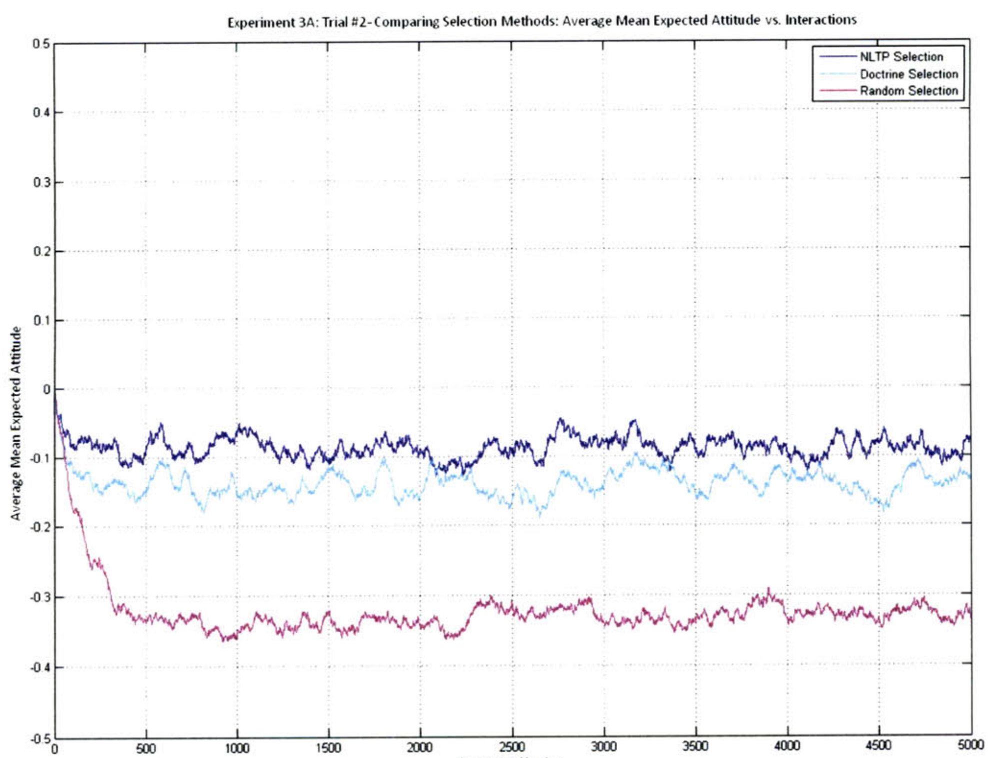

Figure B- 18: Simulation Performance, Experiment 3A, Case #2

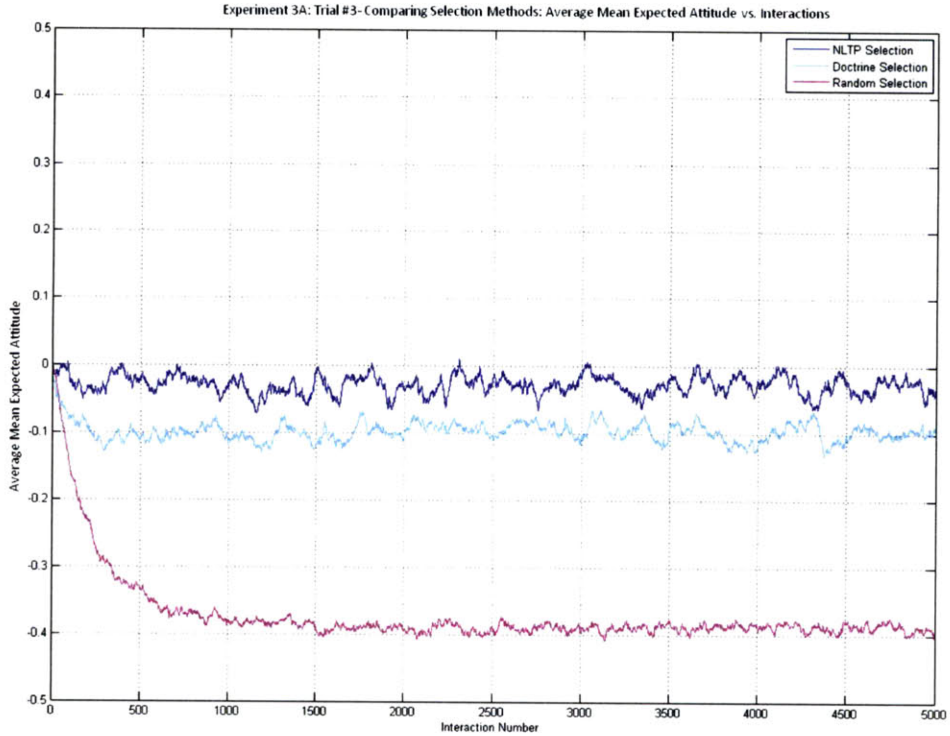

Figure B- 19: Simulation Performance, Experiment 3A, Case #3

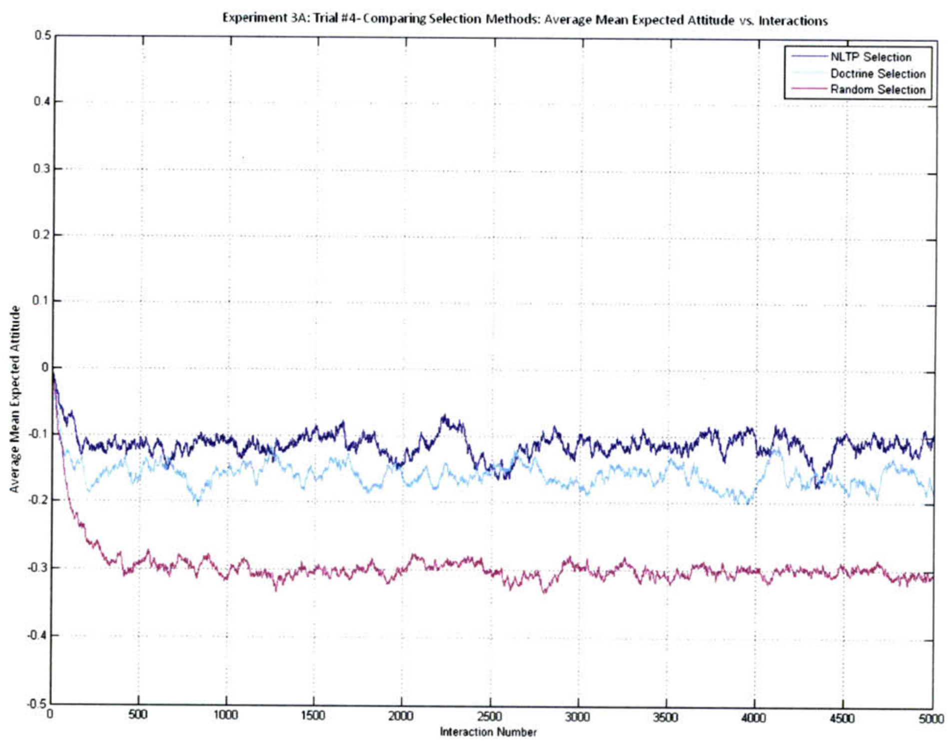

Figure B- 20: Simulation Performance, Experiment 3A, Case #4

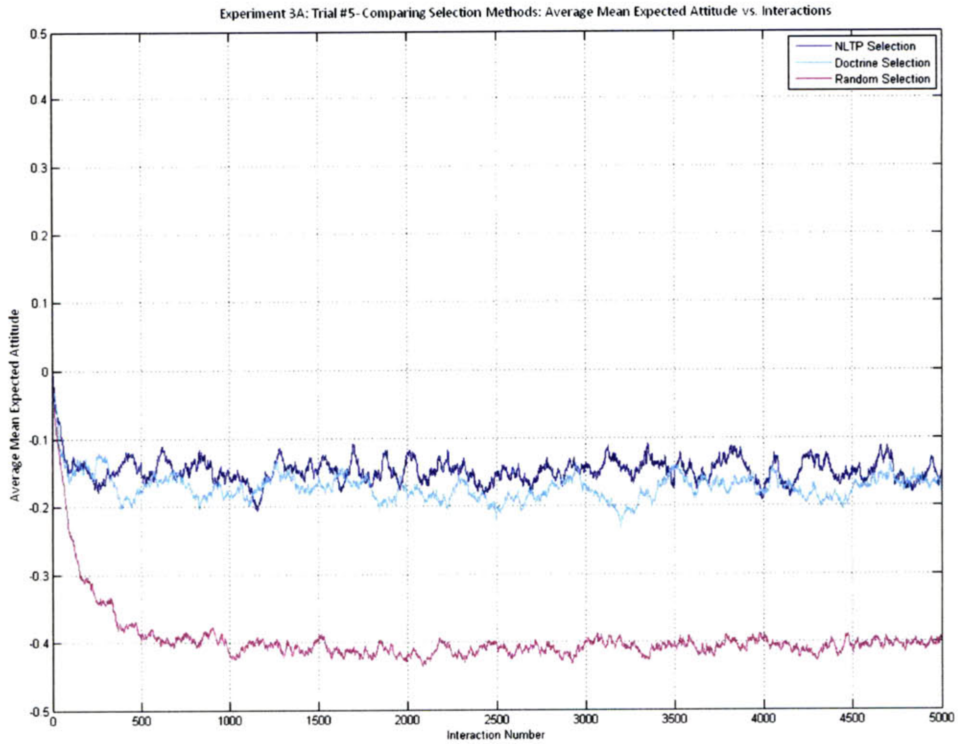

Figure B- 21: Simulation Performance, Experiment 3A, Case #5

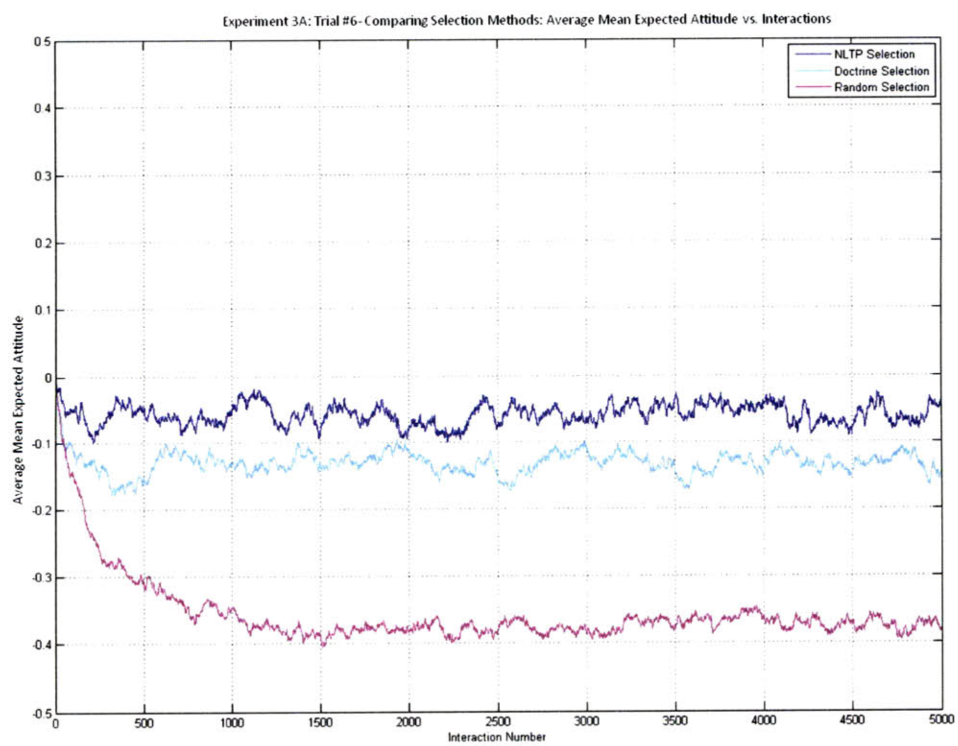

Figure B- 22: Simulation Performance, Experiment 3A, Case #6

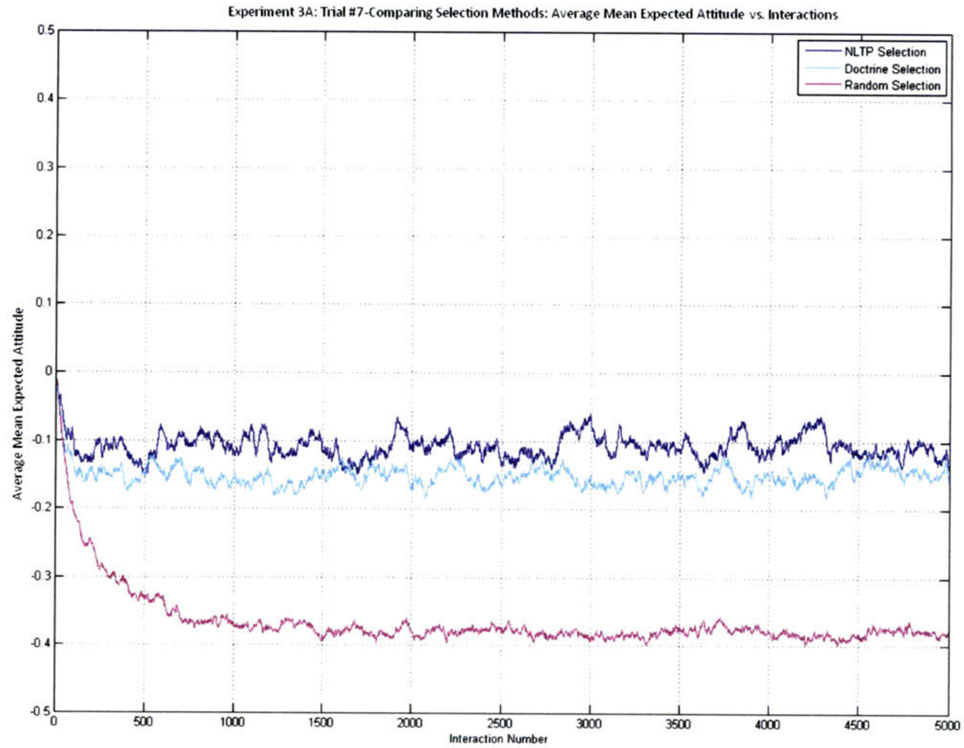

Figure B- 23: Simulation Performance, Experiment 3A, Case #7

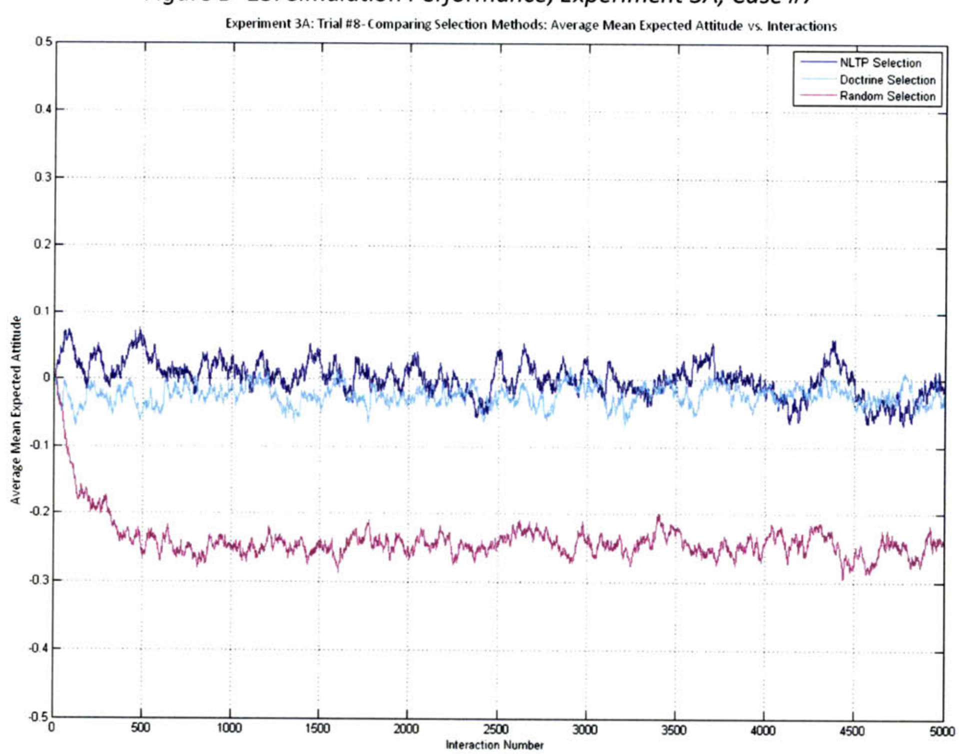

Figure B- 24: Simulation Performance, Experiment 3A, Case #8

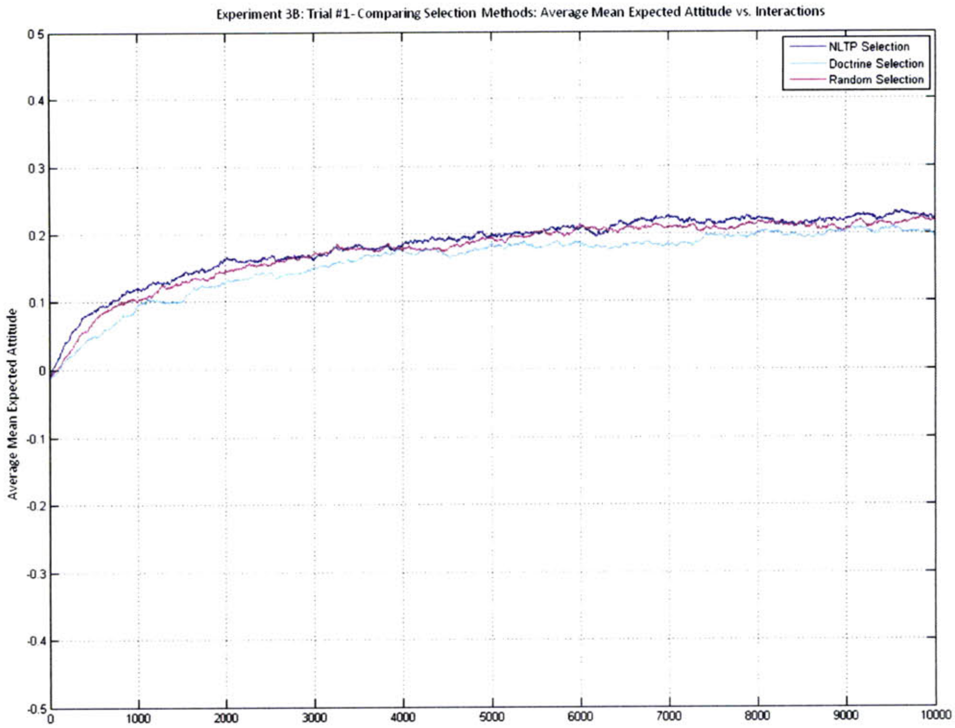

Figure B- 25: Simulation Performance, Experiment 3B, Case #1

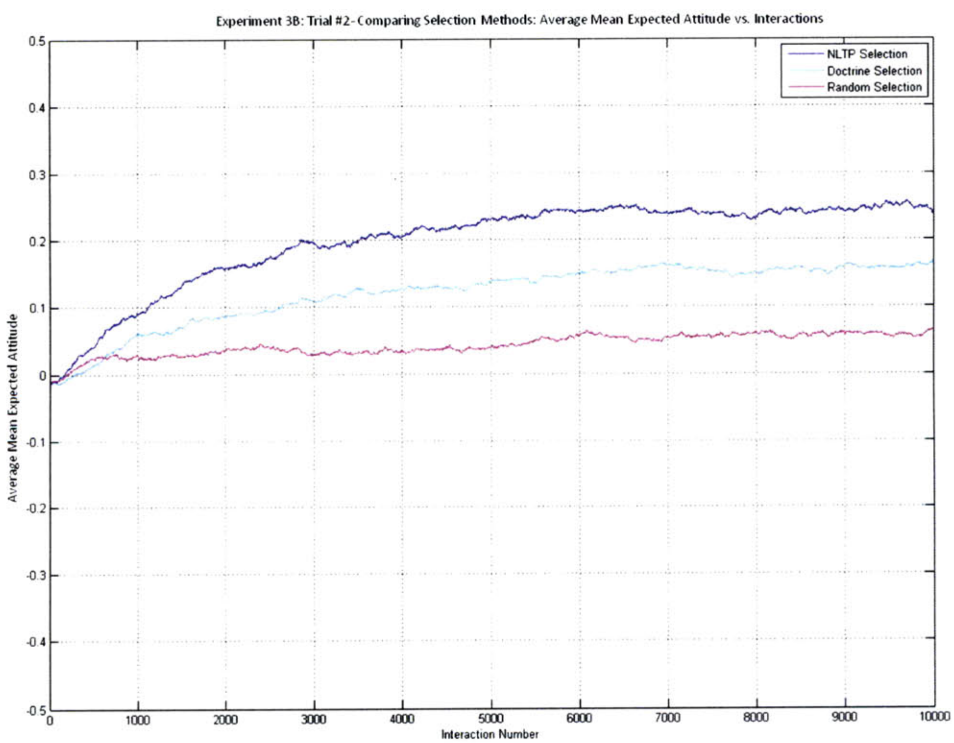

Figure B- 26: Simulation Performance, Experiment 3B, Case #2

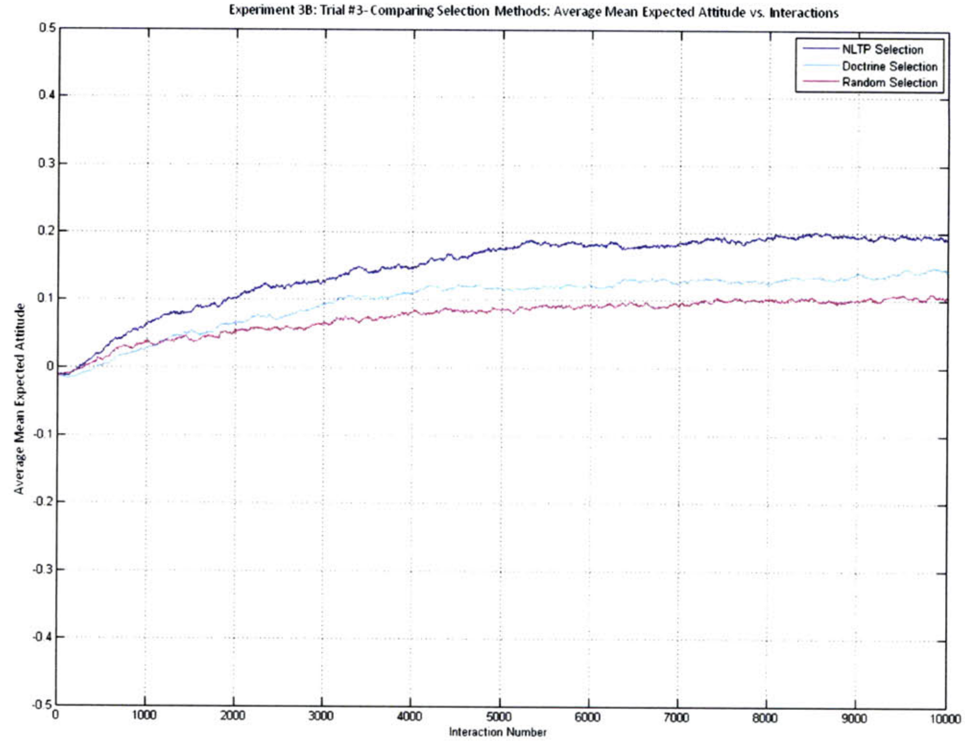

Figure B- 27: Simulation Performance, Experiment 3B, Case #3

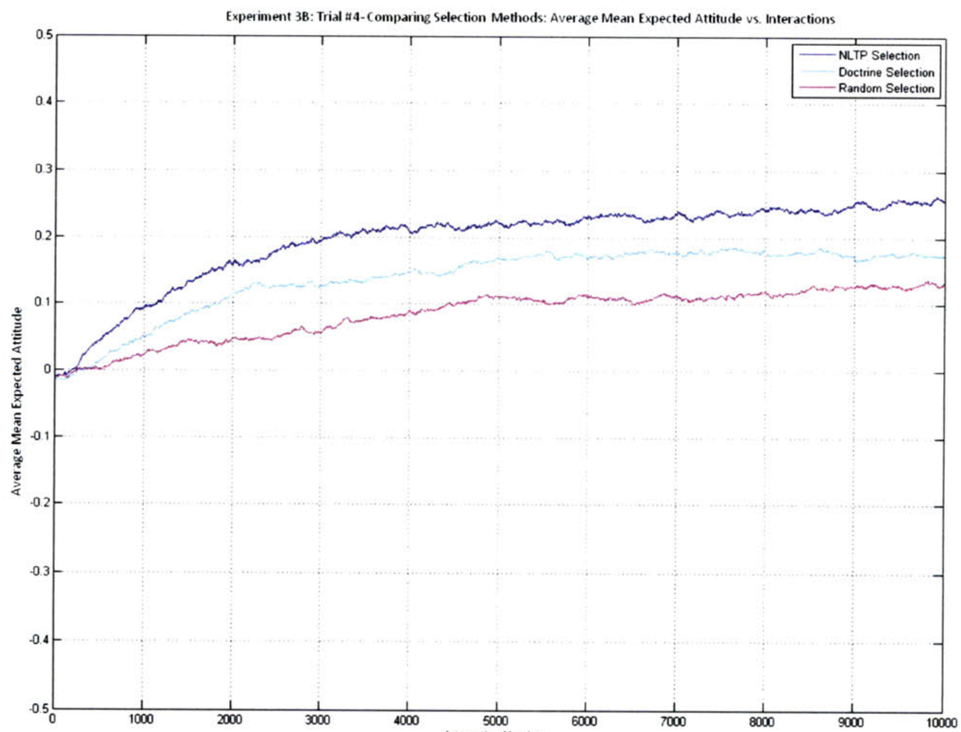

Figure B- 28: Simulation Performance, Experiment 3B, Case #4

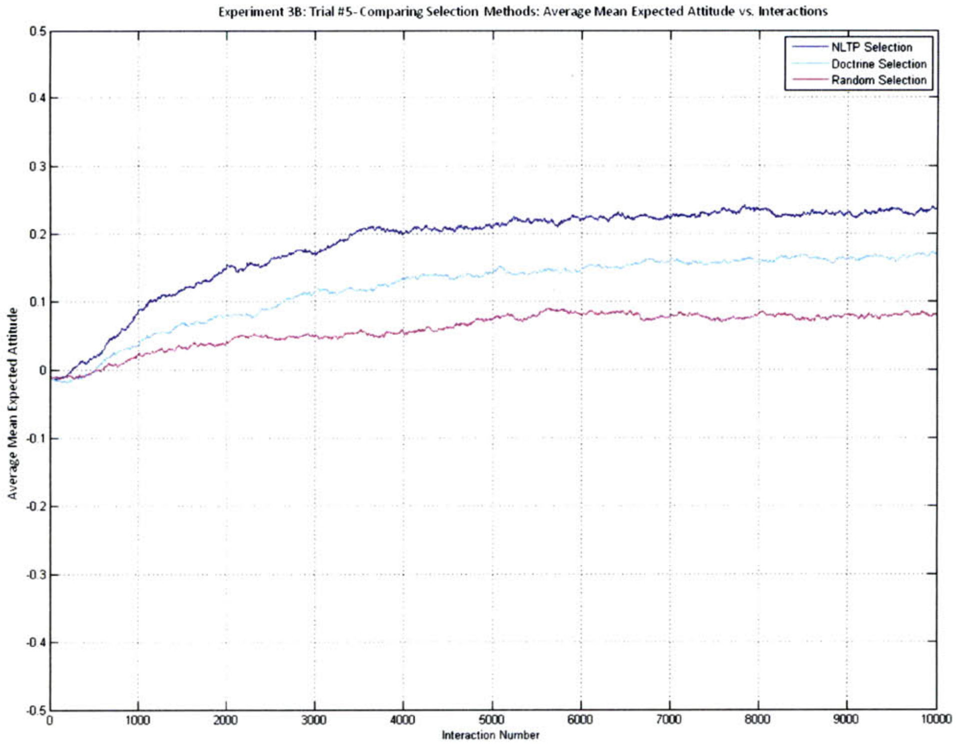

Figure B- 29: Simulation Performance, Experiment 3B, Case #5

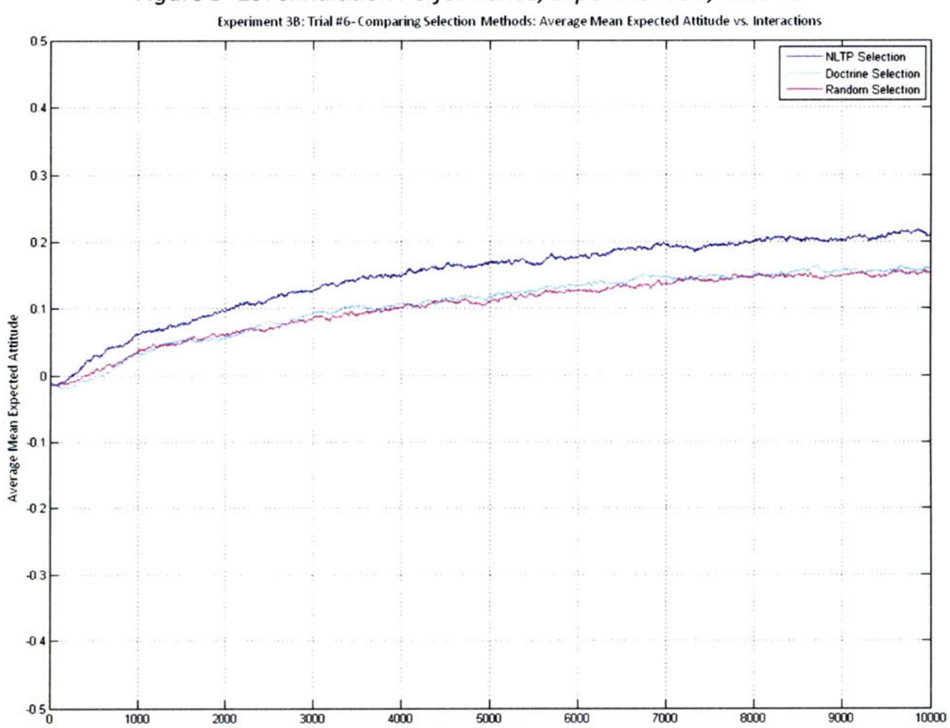

Figure B- 30: Simulation Performance, Experiment 3B, Case #6

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